Implications of Disclosing Order Backlog

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Abstract

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Features of the requirement to disclose order backlog raise questions about the usefulness of these disclosures in practice. Despite these concerns, I provide evidence that disclosing the dollar amount of order backlog in the 10-K has several implications for firms in the manufacturing sector. On average, firms that disclose order backlog have significantly higher forward earnings response coefficients and greater investment efficiency. These effects, however, are concentrated amongst firms for which order backlog is expected to be a stronger signal of demand (i.e., firms that follow more of a make-to-order business model). Disclosers also have less persistent operating profitability when order backlog is a relatively more important signal of demand, suggesting that although order backlog can provide useful information for valuation and monitoring purposes, it can also influence competitors' product market and investment decisions. The results should be of interest to regulators as they examine Regulation S-K disclosure requirements, and firms and standard setters as they prepare for greater forward-looking revenue disclosures under ASC 606.

1. Introduction

Regulation S-K requires all U.S. public firms to disclose the dollar amount of "…orders believed to be firm…" in Item 1 of the 10-K (Description of Business).[1] This information is often referred to as order backlog and has the unique feature of being a quantitative forward-looking mandatory disclosure about demand. Accordingly, stakeholders interested in understanding the future prospects of a firm are likely to find order backlog information useful in their decision-making.

Despite the conceptual usefulness of order backlog information, features of the disclosure requirement could limit whether this information influences stakeholders' decisions. In particular, there is no precise definition of a "firm" order and limited additional disclosure requirements. For example, firms often include cancellable orders in the reported dollar amount of backlog; however, the disclosures do not typically contain information about historical or expected rates of cancellation. Recent comment letters from the Securities and Exchange Commission (SEC) reveal a concern that the absence of supplementary information reduces the usefulness of these disclosures (Deloitte 2015). Therefore, it is unclear whether backlog disclosures under the current requirement provide useful information to stakeholders, a question also raised in the SEC's April 2016 concept release (SEC 2016).[2]

I investigate whether disclosure of the dollar amount of backlog is useful for stakeholders and thus whether there are implications associated with disclosing this information. Given the nature of backlog as an indicator of demand and future performance, I conjecture that disclosing

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[1] I reproduce the disclosure requirement, which is in Item 101(c)(1)(viii) of Regulation S-K, in Appendix A.1.

[2] Prior research on order backlog examines the information content of the reported dollar amount. These studies find changes in backlog are correlated with relevant economic events (Lev and Thiagarajan 1993), but mixed evidence on whether and how investors incorporate backlog into their decisions (Rajgopal et al. 2003; Feldman et al. 2014). I discuss this research and the relation to my study in section 2.2.1.

backlog could influence the forecasting and valuation decisions of investors, stakeholders' monitoring decisions, and competitors' product market and investment decisions. To test this possibility, I compare the price informativeness, investment efficiency, and persistence of operating profitability of firms that disclose a dollar amount of backlog (disclosers) to firms that have a similar likelihood of having material order backlog but do not disclose a dollar amount of backlog in the 10-K (non-disclosers).[3]

Examining the usefulness of backlog disclosures is timely as regulatory activities indicate a move toward greater forward-looking revenue disclosures. In particular, although disclosers are concentrated in the manufacturing sector, the SEC has requested firms operating in other industries, such as those with subscription-based business models, provide backlog disclosures. For instance, Salesforce.com Inc. received an SEC comment letter that requested clarification for why the company did not report the total contract value for non-cancelable subscriptions, which appeared to meet the SEC's interpretation of order backlog. Furthermore, the upcoming adoption of ASC 606 (Revenue from Contracts with Customers) will lead to similar disclosures in the footnotes to the financial statements.[4] As these disclosures become more prevalent in firms' mandatory filings, it is important for firms, standard setters, and regulators to understand whether disclosing backlog influences stakeholders' decisions and the related consequences for firms.

A significant feature of the backlog disclosure requirement is the ambiguity about whether a firm should disclose this information. This ambiguity partially stems from the absence of both a precise definition of order backlog and a specific materiality threshold for disclosure. An

[3] I do not use information about the magnitude of order backlog in my primary empirical tests because I am interested in *whether* this disclosure is incrementally useful to stakeholders rather than *how* stakeholders react to the information content of backlog (i.e., the amount).

[4] Paragraphs 606-10-50-13 through 606-10-50-15 of ASC 606 outline that firms will be required to disclose the aggregate amount of the transaction price associated with unsatisfied performance obligations of customer contracts and the timing over which the firm expects to recognize the revenue associated with these obligations.

important consequence of this uncertainty is that it allows for variation in firms' backlog disclosure policies independent of the existence of order backlog. For example, although Deere and Co. and AGCO Corporation operate in the same industry and report each other as direct competitors, only Deere and Co. discloses backlog. Furthermore, as backlog disclosures are not part of the financial statements, auditors are not responsible for ensuring compliance with this requirement. That non-disclosure does not necessarily imply non-existence of order backlog offers an opportunity to examine the implications of disclosing backlog per se.

I use a sample of firms from 15 manufacturing industries in which backlog is commonly disclosed over the period 1996-2014. I focus on these industries for two reasons. First, I expect that non-disclosure is less likely to imply non-existence of order backlog, which enables me to investigate the effects of *disclosing* backlog. Second, if the proportion of firms disclosing backlog is an indication of the relevance of the information, I expect any effects of disclosure to be strongest in these industries, in which the proportion of disclosers ranges from 37.8% to 95.3%.

Although I select a sample of firms from industries in which I expect non-disclosure is not attributable to non-existence, a firm's backlog disclosure policy is not randomly determined. Moreover, because backlog is a mandatory disclosure, firms' disclosure policies exhibit little to no time-series variation. Thus, I rely on cross-sectional variation in firm outcomes to infer the effects of disclosing backlog, which raises concerns that fundamental differences between disclosers and non-disclosers could represent omitted variables in my analyses. To mitigate these concerns, I also use propensity score matching to create a matched sample of firms with similar characteristics but different backlog disclosure policies.

Some commentators have criticized the backlog disclosure requirement by arguing backlog information is not relevant for all firms (SEC 2016). This is a valid criticism when considering certain sectors (e.g., retail), but also potentially applies in the context of the manufacturing sector. Manufacturing firms can produce goods to hold in inventory ("make-to-stock"), or begin production when a purchase order is received ("make-to-order"). I conjecture that backlog is a less relevant signal of demand and therefore less likely to influence stakeholders' decisions when a firm adheres more closely to a make-to-stock business model. Therefore, I also test whether any implications of disclosing backlog vary with the expected relevance of the information (i.e., the type of business model a firm follows).

I first examine whether disclosing backlog is associated with investors' forecasting and pricing decisions. All else equal, if order backlog information changes investors expectations of future earnings, current period returns should reflect a greater amount of future earnings information for firms that disclose backlog (i.e., disclosers should have a stronger correlation between current returns and future earnings). Consistent with backlog providing information that is useful for investors' forecasting and valuation decisions, disclosers have significantly higher forward earnings response coefficients than non-disclosers. This result, however, is concentrated amongst make-to-order firms. These findings provide evidence of a potential capital market benefit associated with disclosing backlog—greater price informativeness.

Publicly disclosing the dollar amount of backlog could reduce information asymmetry between managers and stakeholders that monitor managers' investment decisions. If monitors have information about ex ante demand (i.e., backlog) and use this information to evaluate managers' investment decisions, managers could invest more efficiently. I find that the investment expenditures of disclosers are significantly more sensitive to their investment opportunities, suggesting that disclosing backlog is associated with greater investment efficiency. Although this result holds on average, it is driven by the greater investment efficiency of make-to-order firms. Overall, the evidence is consistent with managers anticipating greater scrutiny over the quality of their investment decisions if they disclose backlog and this is a more important signal about the firm's demand and investment opportunities. Thus, disclosing backlog can provide monitoring benefits to a firm by reducing agency costs.

I next examine whether backlog is useful for competitors in their product market and investment decisions. It is plausible that disclosing backlog reduces uncertainty about demand. Lower uncertainty about demand could allow competitors to make decisions that reduce the persistence of a firm's operating profitability (i.e., faster mean reversion). For instance, positive profitability shocks accompanied by strong backlog could encourage competitors to enter or expand operations in the firm's product market. I find that disclosing backlog is negatively associated with the persistence of operating profitability for firms in which backlog is expected to provide a more relevant signal of demand (i.e., make-to-order firms). This result suggests that backlog could provide useful information to competitors, leading to a more competitive environment for certain firms (e.g., Stigler 1963; Dickinson and Sommers 2012; Li et al. 2013). Thus, although there are capital market and monitoring benefits associated with disclosing backlog, there could also be proprietary costs associated with this disclosure.

An important attribute of the backlog disclosure setting is that it provides an opportunity to examine the effects of disclosure per se (because non-disclosure does not necessarily imply non-existence of order backlog). Identification of these effects presents certain challenges however. Most notably, because firms typically maintain a consistent disclosure policy, differences between disclosers and non-disclosers raise the possibility of omitted variables. Although I attempt to address these concerns through several features of my empirical design (e.g., examining the robustness of inferences to the use of a matched sample), in the absence of significant regulatory costs of non-compliance, one unobservable difference between disclosers and non-disclosers could be the perceived net benefits of disclosing backlog (i.e., disclosers could be those firms that anticipate greater net benefits from disclosing backlog).[5] Although this difference would reduce the generalizability of my inferences, it should not affect my interpretation of the results. Nonetheless, I acknowledge that without exogenous variation in whether a firm discloses order backlog, I cannot rule out the possibility of omitted variables and alternative interpretations.

My study contributes to at least three streams of existing literature. First, I provide evidence of how a firm's backlog disclosure policy can influence various stakeholders' decisions, contributing to an extensive literature on the costs and benefits of disclosure (see Beyer et al. 2010 for a review). Concerns about excessive corporate disclosures underscore the importance of assessing the usefulness of existing disclosure requirements (White 2013; Leuz and Wysocki 2016). Second, my results demonstrate the usefulness of order backlog disclosures for purposes other than forecasting valuation, which has been the primary focus of prior literature on order backlog (e.g., Rajgopal et al. 2003; Feldman et al. 2014). Finally, while a number of prior studies investigate the *determinants* of non-compliance with mandatory disclosure requirements (e.g., Gleason and Mills 2002; Robinson et al. 2011; Ayers et al. 2015), my study provides evidence on several *consequences* of non-compliance (e.g., less informative prices). Furthermore, as

[5] The high rates of non-compliance suggest that the regulatory costs of non-compliance for non-disclosers are not particularly high. However, I expect that stopping disclosure would be relatively more costly for disclosers because the firm has already signaled the existence of material backlog information. This reasoning also provides an explanation for why disclosers potentially bear negative competitive consequences from disclosing backlog (because they are committed to the disclosure policy before my sample period).

forward-looking revenue disclosures become more prevalent in firms' financial filings, my results should be informative to firms, standard setters, and regulators.

In summary, disclosing the dollar amount of order backlog is associated with stakeholders' implied decisions when backlog is a particularly important signal of demand, despite these disclosures often lacking details that would assist with interpreting the dollar amount. However, further work is required to understand whether firms can increase the usefulness of these disclosures by providing additional information. The finding that disclosing backlog is associated with firm-level consequences also highlights several opportunities for future research. For instance, I provide preliminary evidence that backlog disclosures could improve the credibility of management forecasts. However, further research is required to understand these relations as well as whether and how backlog disclosures are associated with other operational and reporting decisions.

2. Background and hypotheses development

2.1. Institutional details and related literature

Regulation S-K requires all U.S. public firms to disclose the dollar value of material "…orders believed to be firm…" These orders are commonly referred to as "order backlog" and represent orders a company has received but not yet fulfilled.[6] Because the dollar amount of order backlog is typically recognized in revenue in subsequent periods, this information can provide a leading indicator of performance. Empirical evidence is largely consistent with this notion; prior literature documents that, on average, the level of and changes in order backlog are

[6] No cash has to be received to include the amount of an order in the dollar amount of reported backlog. In fact, only 27.6% of disclosers in my full sample report non-zero deferred revenue and the dollar amount of backlog is greater than deferred revenue for 93.3% of these firms. This suggests order backlog typically includes a broader set of orders than those for which cash has been received.

positively associated with future performance (Rajgopal et al. 2003; Steele and Trombley 2012).[7] Moreover, Lev and Thiagarajan (1993) find that changes in order backlog relative to changes in sales are positively associated with contemporaneous returns, suggesting backlog provides or at least is correlated with relevant information about firm performance.[8] Therefore, backlog could provide useful information to stakeholders interested in understanding the future prospects of a firm.

Although there are conceptual and empirical reasons to expect backlog disclosures would convey useful information to stakeholders, there are several reasons this information might not influence their decisions. First, practical implications of the requirement in Regulation S-K could reduce the usefulness of backlog disclosures. Specifically, because of ambiguity about what constitutes a "firm" order, the definition of order backlog can vary across, and even within, firms. For example, some firms interpret "firm" orders to include only those amounts pertaining to non-cancellable orders, while others report backlog associated with cancellable orders. Moreover, beyond disclosing the dollar amount of backlog and the portion the firm does not expect to fulfill within the current fiscal year, firms are not required to, and typically do not, disclose additional details about the features of the orders that make up the reported dollar amount (see Appendix A for example disclosures). For instance, if backlog includes amounts associated with cancellable orders, the disclosure does not usually specify the expected impact of cancellation on the conversion of backlog to revenue. Recent trends in SEC comment letters reinforce concerns about the usefulness of these disclosures, with SEC staff requesting more

[7] Although it is possible that a positive change in backlog is a negative signal of firm operations, provided these orders are subsequently fulfilled, amounts in order backlog should be positively associated with future revenue. I confirm this intuition and the results from prior research by documenting that changes in backlog are positively associated with future sales growth and future earnings on average in my sample (see Appendix E for results).

[8] Francis et al. (2003) do not find that backlog explains contemporaneous returns in the homebuilding industry.

information about how backlog is defined, calculated, and any changes in the methodology used to compute amounts in backlog from year to year (Deloitte 2015).

Second, stakeholders could rely on other information such that order backlog disclosures are not incrementally informative. For instance, if backlog information is difficult to process or there is more salient information in a firm's financial filings, stakeholders may not attend to backlog when making decisions (Hirshleifer and Teoh 2003). Similarly, if the proportion of firms that disclose backlog is an indication of the relevance of this information, reporting trends suggest this information may not be useful for stakeholders' decisions in recent years. Specifically, the proportion of firms that disclose order backlog in the manufacturing sector, which is the sector in which backlog is most commonly reported, decreased from 47.0% in 1973 to only 24.8% in 2015 (see Figure 1).

Finally, because the dollar amount of backlog is disclosed under Item 1 of the 10-K and not in the financial statements, auditors are not required to perform substantive audit testing of these disclosures.[9] Less verification over the information could lead stakeholders to disregard the backlog disclosures. Disclosures also often include the caveat that amounts reported in backlog are not a reliable indicator of future revenue. If these statements are an important signal of the perceived usefulness of the disclosure, stakeholders might not rely on the information.

In sum, whether disclosing order backlog under the current disclosure requirement influences stakeholders' decisions is an open empirical question. Prior literature investigates the information content of reported dollar amounts of order backlog with respect to future

[9] AU Section 550, paragraph 4, states: "The auditor's responsibility with respect to information in a document does not extend beyond the financial information identified in his report, and the auditor has no obligation to perform any procedures to corroborate other information contained in a document. However, he should read the other information and consider whether such information, or the manner of its presentation, is materially inconsistent with information…"

performance and market pricing. However, these studies do not directly speak to the effects of *disclosing* order backlog nor provide evidence on whether backlog information is useful for purposes other than forecasting and valuation. Consequently, I develop several hypotheses that investigate whether disclosing the dollar amount of outstanding order backlog is useful for investors in making forecasting and valuation decisions, stakeholders in monitoring managers' investment decisions, and competitors in making product market and investment decisions.[10]

2.2. Hypotheses development

2.2.1. Usefulness of backlog information for investors in forecasting and valuation decisions

I first explore whether disclosing order backlog is associated with investors' forecasting and pricing decisions. Prior literature provides mixed conclusions as to whether investors *accurately* incorporate backlog information into their pricing decisions (Rajgopal et al. 2003; Feldman et al. 2014). Using a Mishkin test, Rajgopal et al. (2003) find the market overweights the implications of the level of order backlog for future earnings, leading to negative abnormal returns over the subsequent twelve months (for a sample period between 1981-1999). Feldman et al. (2014), however, use a more recent sample and document a significant positive association between changes in order backlog and short window returns around earnings announcements. However, these authors find no significant association between the level of and change in order backlog and subsequent monthly abnormal returns. Thus, although backlog is correlated with relevant economic events on average (Lev and Thiagarajan 1993), whether this information changes investors' expectations of future performance and influences their valuation decisions is unclear, particularly in recent years.

[10] Although backlog information could also be useful for other stakeholders such as debtholders, because these stakeholders can create more explicit contracts with the firm, publicly disclosing order backlog is less likely to affect their decisions.

While prior literature investigates whether investors correctly price backlog information, I am interested in whether the existence of the backlog disclosure itself is incrementally useful for investors when forecasting earnings and valuing the firm. Therefore, rather than focusing on a sample of firms that disclose order backlog, I compare the amount of future earnings information reflected in current period returns for disclosers and non-disclosers (i.e., compare the correlation between future earnings and current returns for disclosers and non-disclosers). Holding current period earnings news constant, the extent to which future earnings information is correlated with current period returns provides an assessment of changes in investors' expectations of future earnings. There are two advantages of this empirical approach to infer whether investors use backlog information for forecasting and valuation decisions relative to prior research that associates the level or change in the dollar amount of backlog with returns. First, it does not rely on modeling the relation between backlog and earnings, which could vary across firms, particularly in light of differences in how firms define backlog. Second, it does not require measuring unexpected backlog, which would involve measurement error without an accurate expectation for the level of backlog.[11]

If order backlog provides information that changes investors' expectations about future earnings and in turn influences their pricing decisions, I expect current period returns to reflect a greater amount of future earnings information for firms that disclose backlog. Existing literature finds a positive relation between the amount of future earnings information reflected in current period returns and the transparency of segment disclosures (Ettredge et al. 2005), the provision

[11] The mixed evidence in prior literature further highlights this difficulty. Rajgopal et al. (2003) examine the pricing of the *level* of backlog, which is largely a function of a firm's business model and operating cycle, whereas returns should reflect investors' reactions to *unexpected* backlog. However, because analysts do not forecast backlog, measuring unexpected backlog to conduct pricing tests relies on annual changes (Feldman et al. 2014), which likely involves measurement error. Because of the inconsistent results and methodologies in prior research as well as the difficulties associated with their empirical designs, it is an open question as to *whether* backlog disclosures are incrementally informative for investors in forecasting and pricing future performance.

and characteristics of management forecasts (Choi et al. 2011), and analysts' ratings of firm disclosures (Lundholm and Myers 2002). These results highlight that disclosures can provide information beyond the information contained in current earnings news that change investors' expectations of future earnings and thus demonstrate that a firm's voluntary and mandatory disclosure practices can affect stock price informativeness (i.e., the forward earnings response coefficient).

Despite theoretical arguments for why backlog information could be useful for investors, I discuss several reasons why order backlog may not affect investors' forecasting and pricing decisions in section 2.1. For instance, a lack of detail in backlog disclosures could make it difficult for investors to interpret the implications of backlog for future performance. As a result, disclosing order backlog may not incrementally change investors' expectations of future earnings and have no effect on the degree to which future earnings information is reflected in current returns. Thus, I state my first hypothesis in null form:

H1: Disclosing order backlog is not associated with the extent to which future earnings information is reflected in current period stock returns.

2.2.2. Usefulness of backlog information for stakeholders in monitoring managers' investment decisions

In addition to providing information for valuation purposes, financial disclosures can be useful for monitoring managers' investment decisions and thus serve a stewardship function (Watts and Zimmerman 1986). If managers expect monitors to use backlog information in evaluating the firm's investment opportunities, disclosing order backlog could discipline managers' investment decisions. Therefore, I examine whether the provision of a quantitative backlog disclosure is associated with greater investment efficiency and thus lower agency costs.

The role of financial disclosures in reducing agency costs has been widely documented in the accounting literature (see Armstrong et al. 2010 for a review). Using the change in disclosure requirements under SFAS 131, Hope and Thomas (2008) find firms that do not disclose geographic earnings experience greater sales growth but lower profit margins than disclosing firms. The authors contend that when geographic earnings are not disclosed, it is more difficult for outsiders to connect manager's decision-making to firm performance, increasing a manager's ability to engage in empire building activities. Similarly, Cho (2015) provides evidence that the enhanced segment disclosures of SFAS 131 increased the efficiency of internal capital market allocations. Overall, these studies illustrate how greater reporting transparency can reduce agency costs.

A firm's optimal investment is a function of the extent of demand for its products or services. Disclosing the dollar amount of outstanding order backlog could reduce information asymmetry between managers and external monitors about demand and thus the firm's investment opportunities. Lower information asymmetry could make it more costly for managers to make investment decisions that maximize their own utility at the expense of firm value. For example, all else equal it would be more difficult for managers to rationalize high levels of capital expenditures when demand (i.e., backlog) is low and this is disclosed publicly. Thus, disclosing backlog could reduce moral hazard in managers' investment decisions, resulting in higher investment efficiency for disclosers.

Whether disclosing backlog would reduce agency conflicts, however, is unclear ex ante. In addition to the general concerns I discuss in section 2.1, boards of directors likely have access to backlog information even in the absence of public disclosure. Furthermore, if managers do not believe stakeholders use backlog information in evaluating and monitoring investment decisions, disclosing backlog may not have a significant disciplining effect on their investment behavior. This leads to my second hypothesis:

H2: Disclosing order backlog is not associated with a firm's investment efficiency.

2.2.3. Usefulness of backlog information for competitors in product market and investment decisions

Given the potential relevance of backlog as a signal of demand, competitors could use this information in making product market and investment decisions. Whether and how competitors use these disclosures, however, depends on the signal that backlog provides and the competitive environment the firm operates within (e.g., the nature and source of competitive threats). For example, if two firms knowingly compete for the same set of *fixed* orders, the backlog information of the winning firm is not informative to the firm that missed out.[12]

Order backlog information could decrease uncertainty about the magnitude of aggregate demand or the extent to which incumbent firms have already captured demand. Thus, disclosing the dollar amount of backlog could reduce a competitor's uncertainty about the payoffs from alternative product market and investment decisions (e.g., expansion/contraction or entry/exit). Real option theory predicts that lower uncertainty reduces the threshold for investment (e.g., McDonald and Siegel 1986). Consistent with this theory, Badertscher et al. (2013) document that private firms' investment decisions are more responsive to investment opportunities when there is greater public firm presence and thus, less uncertainty, in the industry. Therefore, if backlog is informative about the permanence of changes in a firm's demand from customers, disclosing this information could enable competitors to make more efficient product market and investment

[12] Under *uncertain* demand, theory provides mixed predictions about the optimality of information sharing. Generally, the predictions for whether firms are better or worse off from sharing their private information about demand depend on the type of competition and assumptions about the cost structure in the industry (e.g., Clarke 1983; Vives 1984; Kirby 1988).

decisions.[13] For instance, disclosers could find it more difficult to protect rents associated with an increase in demand. Similarly, if a firm experiences a decline in demand, disclosing this could deter entry or expansion in the market, which could lead to faster mean reversion in profitability.

Because I am first interested in *whether* disclosing backlog provides useful information to competitors rather than *how* competitors respond to this information (e.g., pricing or investment decisions), I examine the persistence of a firm's operating profitability.[14] This provides a broad measure of the competitive intensity a firm faces (e.g., Stigler 1963; Dickinson and Sommers 2012; Li et al. 2013). Given ambiguous predictions about whether backlog disclosures influence competitors' decisions, I state my final hypothesis in null form:

H3: Disclosing order backlog is not associated with the persistence of operating profitability.

3. Sample and descriptive statistics

3.1. Sample selection and propensity score matching

Investigating the implications of mandatory disclosures is typically complicated by the fact that non-disclosure implies non-existence of the underlying information being examined (Hribar 2004). In the case of order backlog, however, ambiguity in the definition of a "firm" order and differences in materiality thresholds allow for variation in firms' backlog disclosure policies

[13] This argument does not depend on competitors taking actions to compete away profitability shocks. Rather, a credible competitive threat is sufficient to reduce the value of the option to wait in capital investment decisions (Grenadier 2002). For instance, if a firm anticipates competitors entering the market, the firm could make investment or product market decisions that reduce the incentives of competitors to enter (e.g., lower prices).

[14] A common approach in the voluntary disclosure literature to assess whether a firm anticipates that competitors would use a given disclosure is to examine whether competitive concerns are sufficiently high ex ante to prevent firms from disclosing this information (e.g., Botosan and Stanford 2005; Li 2010; Ellis et al. 2012). This approach would be problematic in this setting for at least two reasons. First, similar to prior literature, it is unclear what type of competition (e.g., existing versus potential competitors, innovative versus imitative) would be most likely to affect any discretion managers have over the firm's backlog disclosure policy (Li 2010). Second, because backlog has been a mandatory disclosure since 1973, there is limited managerial discretion over a firm's disclosure policy in my sample period, which would lead to a low power test (Heitzman et al. 2010).

independent of the existence of order backlog. Consistent with this possibility, I find variation in backlog disclosure policies amongst peer firms; although Deere and Co. and AGCO Corporation report each other as direct competitors, only Deere and Co. discloses backlog. Similarly, toymaker Mattel Inc. has never reported backlog, but Hasbro Inc., a key competitor, reported backlog until 2010. These anecdotes suggest that firms with similar characteristics (e.g., products, business models) can have different backlog disclosure policies, providing an opportunity to examine the effects of *disclosing* backlog.

Despite the theoretical ability to test for the consequences of disclosure per se, identification of these effects presents certain empirical challenges. In particular, because disclosing backlog is a mandatory requirement, firms typically commit to a particular disclosure policy. In fact, the vast majority of firms in my sample are sticky disclosers (see Figure 2). This means I rely on cross-sectional variation in firm outcomes to infer the effects of disclosure. Furthermore, because a firm's backlog disclosure policy is not randomly assigned, any systematic differences between disclosers and non-disclosers could raise concerns about omitted variables when making comparisons between these groups of firms.

Clearly the existence of material order backlog is a necessary condition for disclosure and potentially represents an important difference between disclosers and non-disclosers. For this reason, I select a sample of firms from industries in which I expect non-disclosure is less likely to imply non-existence. Specifically, I focus on manufacturing industries in which the average proportion of U.S. firms that disclose order backlog each year for the period 1996-2014 is at least 25%. I identify firms that disclose a dollar amount of order backlog from Compustat and define industry groups using four-digit NAICS codes. I also use propensity score matching to mitigate the concern that even within these industries, disclosers and non-disclosers represent fundamentally different firms, which could complicate interpretation of my results (see Appendix B for details).

Before estimating the propensity score model, I restrict the sample to firm-years with complete data to estimate the propensity score model and test my hypotheses. I obtain financial statement information from Compustat and returns and pricing data from the Center for Research in Security Prices (CRSP). I drop observations with a price less than $1 three months after the end of fiscal year $t - 1$. To reduce the impact of influential observations on my analyses, I truncate the sample at the 1st and 99th percentiles of firm stock returns in year t and $t + 1$ and drop observations for which earnings scaled by market value of equity in years $t - 1$, t, or $t + 1$ is greater than one in absolute value (Tucker and Zarowin 2006; Choi et al. 2011). Similarly, I exclude observations that have return on net operating assets in year t or $t + 1$ greater than one in absolute value. Finally, I limit the sample to industries in which there are at least 300 firm-year observations over the sample period to increase the likelihood of finding appropriate matches. These restrictions yield a sample of 11,680 firm-year observations from 15 industries, which I refer to as the full sample throughout my analyses. I summarize the sample selection criteria in Appendix C

I use the full sample to also create a matched sample of disclosers and non-disclosers using propensity score matching. I estimate the propensity score model using a logit regression in which the dependent variable equals one if the firm discloses a dollar amount of order backlog in year t and zero otherwise ($Discloser_{it}$). Because firms typically commit to a disclosure policy, I use independent variables that represent relatively persistent firm characteristics such as proxies for a firm's business model, product type, and revenue function.

I present the results of the propensity score model in Table 1. I find several significant differences between disclosers and non-disclosers. Firms that disclose backlog have a smaller proportion of their total inventory held as finished goods, consistent with these firms following a business model in which revenue is less likely to be generated from finished goods inventory on average. Disclosers also have lower R&D intensity, lower gross margins, and lower absolute accruals. They are more likely to report a government agency customer and are less likely to report non-zero advertising expense. Older firms and those at a growth, mature, or shakeout life cycle stage are more likely to disclose backlog. Despite these differences, Panel A of Figure 3 illustrates overlap in the propensity scores for disclosers and non-disclosers for the full sample (i.e., before matching). Therefore, based on the various characteristics I examine, there are similar firms with different disclosure policies.

Although the propensity scores for disclosers and non-disclosers generally have a common support, because there are more disclosers in the full sample, the distribution is visually different for the two groups of firms. Consequently, average differences between these two groups of firms could present an omitted variable problem throughout my analyses. To mitigate these concerns, I test my hypotheses both on the full sample of firm-years as well as a matched sample. Specifically, I use nearest neighbor matching within a 0.05 caliper to construct a matched sample based on the propensity scores I estimate in Table 1. I match with replacement, which allows for a single control observation to be matched to multiple treatment observations. Because of the overlap in the propensity scores in the full sample, I am able to match a non-discloser with nearly all disclosers in the full sample. The matched sample includes 13,742 firm-year observations. I discuss diagnostics of the matching procedure below.

3.2. Descriptive statistics

I provide summary information for the industries in Appendix C. Across the 15 industries in the full sample, the proportion of disclosers ranges from 37.8% to 95.3% (Panel A). There is substantial within and across industry variation in the backlog intensity of disclosers (backlog as a proportion of sales; $Backlog_{it}$). For instance, in the Communications Equipment Manufacturing industry, the average backlog intensity over the sample period is 0.369, with a standard deviation of 0.383. Across industries, the average backlog intensity ranges from 0.133 to 1.077. The industry composition of the matched sample is notably different because matching with replacement allows a single non-discloser to be matched to multiple disclosers. The average proportion of disclosers in each industry varies from 42.1% to 59.2% in the matched sample, which implies that the closest matches based on the propensity score are often found outside the firm's industry. Overall, Appendix C illustrates the economic significance of amounts reported in backlog and highlights variation in the backlog disclosure practices of firms within and across industries.

I present descriptive statistics in Table 2. In Panel A, I provide summary statistics for all firm-years in the full sample. Overall, 59.4% of this sample discloses order backlog and 8.4% (47.9%) reports a government agency (corporation) as a major customer. The mean (median) magnitude of finished goods inventory is 34.5% (31.0%) of total inventory (after setting missing values to zero). Examining the life cycle stages of my sample firms, 40.7% of the firm-years are in a mature stage, 30.5% in a growth stage, and only 5.6% are in a decline stage. On average, firms in the full sample invest 4.9% of year *t* sales in capital expenditures in year *t* + 1. Approximately 28.2% of the full sample reports negative income before extraordinary items in year *t*, with an average (median) return on net operating assets of 12.2% (13.3%) in year *t*.

Summary statistics for the matched sample, which I present in Panel B, reveal several differences in the average characteristics of the full and matched samples. For instance, firm-years in the matched sample are weighted such that the average firm has less finished goods inventory, is less likely to report advertising expense, is smaller but also slightly older, and is more likely to report a government customer than the average firm in the full sample.

In Panel C, I compare average firm characteristics for disclosers and non-disclosers for the full and matched samples. Consistent with the results in Table 1, the average differences in many of the independent variables in the propensity score model between disclosers and non-disclosers are significantly different from zero in the full sample. However, these differences are not significantly different form zero in the matched sample, highlighting the effectiveness of the match (see also Figure 3, Panel B). I also calculate the standardized difference in means for each variable. This measure represents the difference in the mean values between disclosers and non-disclosers, scaled by the standard deviation of disclosers in the full sample. Because the denominator does not change across the different samples, this provides an across sample comparison of the match effectiveness. In the full (matched) sample, seven (none) of the standardized differences for the propensity score covariates are greater than 0.25 in absolute value, which is often used as a threshold for a satisfactory match (Stuart 2010).

3.3. Predictive strength of backlog for future revenue

I examine the nature of backlog as a leading indicator of future revenue by testing the predictive strength of backlog for future sales and comparing it with inventory, another important signal of future revenue in the manufacturing sector (Steele and Trombley 2012). Specifically, I regress future sales growth ($\%\Delta Sales_{it+1}$) on the growth in 1) backlog intensity ($\%\Delta Backlog_{it}$), 2) total inventory relative to sales ($\%\Delta Inventory_{it}$), and 3) both backlog and inventory. I find that growth in backlog intensity explains approximately 9.9% of future sales growth, on average, within my sample of disclosers, which is over four times higher than the 2.3% explained by growth in inventory (see Appendix E). A Vuong test confirms the statistical significance of the difference in the explanatory power of each signal (p-value = 0.000). Although the signals contain incremental information to one another, as demonstrated by significant coefficients on both when in the same regression specification, backlog growth is more strongly associated with future sales growth than inventory growth on average (p-value = 0.023).

4. Empirical design and results

4.1. Test of hypothesis 1: future earnings information in current returns

In my first hypothesis I examine whether backlog information changes investors' expectations of future earnings such that disclosing backlog is associated with the extent to which future earnings information is reflected in current period returns. To test this possibility, I employ the methodology of Collins et al. (1994) and modified by Lundholm and Myers (2002) and estimate the following model using OLS:

$$
\begin{aligned}
Ret_{it} = {} & \beta_0 + \beta_1 Earn_{it-1} + \beta_2 Earn_{it} + \beta_3 Earn_{it+1} + \beta_4 Ret_{it+1} + \beta_5 Earn_{it-1} \times Discloser_{it} + \\
& \beta_6 Earn_{it} \times Discloser_{it} + \beta_7 Earn_{it+1} \times Discloser_{it} + \beta_8 Ret_{it+1} \times Discloser_{it} + \\
& \beta_9 Discloser_{it} + e_{it} \qquad (1)
\end{aligned}
$$

I measure Ret_{it} as the firm's 12-month buy-and-hold return ending three months after the end of fiscal year t – 1. I define earnings as income before extraordinary items and scale all earnings variables by market value of equity three months after the end of fiscal year t – 1. Because amounts in backlog primarily pertain to orders for the subsequent year, I focus on one-year-ahead earnings. Within the context of equation 1, the sum of the coefficients on future earnings ($Earn_{it+1}$) and future returns (Ret_{it+1}) represents changes in expectations about future earnings in the current period.[15] Therefore, if disclosing backlog changes investors' expectations about future earnings and influences their pricing decisions, I expect ($\beta_7 + \beta_8$) > 0. Throughout the paper I refer to the sum of these coefficients as the forward earnings response coefficient (hereafter "FERC") for parsimony. Given the panel structure of the data, I cluster standard errors by firm and year (Petersen 2009; Gow et al. 2010). I present the results in Table 3, Panel A.

I first examine the results for the full sample. I find that disclosers have significantly higher FERCs relative to non-disclosers (column 2), consistent with order backlog information influencing investors' forecasting and pricing decisions. On average, the coefficient on future earnings (β_3) is higher than that on current earnings (β_2), which is consistent with my sample comprising industries that have higher FERCs on average (Warfield and Wild 1992). In columns 3 and 4, I examine the robustness of my inferences to the inclusion of various control variables. First, I control for several determinants of FERCs documented in prior literature – analyst coverage, operating loss, negative returns, book-to-market, market beta, and firm size (e.g., Lundholm and Myers 2002; Ettredge et al. 2005). Specifically, I interact the earnings and returns independent variables in equation 1 with these control variables. Second, I control for the independent variables in the propensity score model (hereafter "matching controls") to account for the possibility that systematic differences between disclosers and non-disclosers represent an omitted variable. In both cases, the results are robust to these additional controls.[16] I present the results for the matched sample in columns 5-8 and inferences are unchanged.

[15] Similarly, lagged and current earnings are included as proxies to capture unexpected earnings for year *t*. See Lundholm and Myers (2002) for a detailed description of the model.

[16] I do not present the coefficient estimates for the control variables due to the number of additional parameters. In untabulated analyses I also include each of the FERC controls separately and inferences are unchanged; disclosers have significantly higher FERCs than non-disclosers. I find similar inferences when I include both the FERC and matching controls in the same model. I also find similar inferences when I interact the earnings and returns independent variables with the matching controls but do not present these results because the number of additional correlated control variables raises multicollinearity concerns with these results.

A firm's business model likely determines the relevance of a signal for forecasting performance. For instance, firms that adhere more closely to a make-to-stock business model likely derive a smaller proportion of demand from order backlog. As a result, I expect that backlog would be a relatively less useful signal in forecasting future performance for these firms and disclosing this information is less likely to change investors' expectations about future earnings. I proxy for firms that follow more of a make-to-stock business model using an indicator variable equal to one if the proportion of total inventory held as finished goods ($FinishedGoods_{it}$) is greater than 0.50 and zero otherwise (MTS_{it}).[17] I then estimate equation 1 separately for firms based on this split and present the results in Table 3, Panel B. For both the full and matched samples, I find that disclosing backlog is only associated with higher FERCs for firms that follow a make-to-order ($MTS_{it} = 0$) business model.

Overall, the results in Table 3 suggest that order backlog provides useful information to investors in forecasting and valuing the firm, highlighting a potential capital market benefit associated with disclosing backlog—greater price informativeness. Intuitively, this benefit is concentrated amongst firms for which order backlog is a more relevant signal of demand.

4.2. Test of hypothesis 2: investment efficiency

My second hypothesis explores whether backlog provides information that is useful for monitoring managers' investment decisions. To test this hypothesis, I examine whether disclosing order backlog is associated with a firm's investment efficiency where I measure investment efficiency as the sensitivity of investment expenditures to investment opportunities

[17] Because I cannot observe the materiality of order backlog for non-disclosers, I rely on a business model proxy to differentiate firms for which I expect backlog is a more or less relevant signal. However, I find that backlog intensity (amongst disclosers) is significantly lower for firms that I classify as make-to-stock firms (i.e., $MTS_{it} = 1$). Moreover, I find that the coefficient on backlog growth is not significantly different from the coefficient on inventory growth when predicting future sales growth for make-to-stock firms (see Appendix E for results). These results provide corroborating evidence that backlog is a less relevant signal of demand for make-to-stock firms.

(Badertscher et al. 2013; Shroff et al. 2013). Specifically, following prior research I estimate the following regression model using OLS:

$$Capex_{it+1} = \beta_0 + \beta_1 TobinsQ_{it} + \beta_2 TobinsQ_{it} \times Discloser_{it} + \beta_3 Discloser_{it} + \Gamma Controls_{it} + e_{it+1} \qquad (2)$$

I define $Capex_{it+1}$ as capital expenditures in fiscal year $t + 1$ divided by sales in fiscal year t and use Tobin's Q as a proxy for a firm's investment opportunities (e.g., Hubbard 1998; Badertscher et al. 2013). Following prior literature, I control for several determinants of a firm's investment (Biddle et al. 2009). If disclosing backlog is informative about the firm's investment opportunities and this disciplines managers' investment decisions, I expect the investment outlays of disclosers to be more sensitive to investment opportunities than non-disclosers (i.e., $\beta_2 > 0$).

I present the results of estimating equation 2 in Table 4, Panel A. In the full sample I find a stronger positive association between a firm's Tobin's Q and capital expenditures for disclosers than non-disclosers. This association is robust to controlling for the matching controls (column 2) and also holds in the matched sample (columns 3-4). These results are consistent with disclosing backlog reducing information asymmetry between monitors and managers about the firm's investment opportunities, in turn disciplining managers to make more efficient investment decisions.

I also explore whether the disciplining effect of disclosing backlog varies with the expected ex ante relevance of backlog information. In particular, I split the sample based on whether I classify the firm as a make-to-stock (MTS_{it} = 1) or make-to-order firm (MTS_{it} = 0). I present the results of this cross-sectional test in Panel B of Table 4. For expositional ease I do not present the coefficient estimates on the investment control variables in this panel. Consistent with the cross-sectional results in Table 3, I find that the greater investment efficiency of disclosers relative to non-disclosers exists only amongst firms that I classify as make-to-order. This result holds across both the full and matched samples and suggests that backlog only provides useful information for stakeholders in monitoring the investment decisions of managers of make-to-order firms.

Overall, these findings are consistent with managers anticipating that monitors could use backlog information as a way to assess the quality of investment decisions. Therefore, disclosing order backlog provides a monitoring mechanism for managers' investment decisions and highlights another potential benefit of disclosing backlog—lower agency costs.

4.3. Test of hypothesis 3: persistence of operating profitability

In my final hypothesis I explore whether backlog is useful for competitors in making product market and investment decisions such that firms that disclose this information have less persistent operating profitability. Specifically, I calculate operating profitability using return on net operating assets (*RNOA*) and estimate the following regression model using OLS:

$$RNOA_{it+1} = \beta_0 + \beta_1 RNOA_{it} + \beta_2 RNOA_{it} \times Discloser_{it} + \beta_3 Discloser_{it} + e_{it+1} \quad (3)$$

Following prior literature, I calculate $RNOA_{it}$ as operating income after depreciation divided by average net operating assets (Nissim and Penman 2001; Soliman 2008; Fairfield et al. 2009; Curtis et al. 2015). To test my hypothesis, I examine the significance of β_2, which captures the effect of disclosing backlog on the persistence of operating profitability (i.e., the difference in the persistence of operating profitability for disclosers relative to non-disclosers). Following prior literature, I interpret a negative coefficient on β_2 to suggest disclosers experience greater competition on average (Lev 1983; Li et al. 2013).

I provide the results of estimating equation 3 in Table 5, Panel A. I first examine the differential persistence of operating profitability for disclosers and non-disclosers without including any additional control variables. In the full sample I find an average persistence coefficient for non-disclosers (disclosers) of 0.688 (0.666); however, this difference is not significant (column 1). When I include the matching controls (including year and industry fixed effects) to account for any differences in the average profitability of disclosers and non-disclosers, the average differential persistence for disclosers and non-disclosers increases but is still not significant at conventional two-tailed levels (β_2= -0.032, p-value = 0.168; column 3).[18] I find slightly stronger but similar results for the matched sample (columns 4-6).[19]

Although I do not find strong evidence that disclosing backlog has negative competitive consequences for firms on average, the results in Tables 3 and 4 demonstrate that the usefulness of backlog disclosures for valuation and monitoring purposes is concentrated in firms for which backlog is a more informative signal of demand (i.e., make-to-order firms). Therefore, I estimate equation 3 separately for make-to-stock and make-to-order firms and present the results in Panel B of Table 5. In both the full and matched samples, I find that disclosing order backlog is negatively associated with the persistence of operating profitability for make-to-order firms (columns 1-2 and 5-6). For instance, excluding all controls variables, the average operating profitability persistence coeffiicent for non-disclosers (disclosers) is 0.712 (0.656) in the matched sample; a difference that is significant at the 10% level (two-tailed).

[18] Although I control for the main effect of differences between disclosers and non-disclosers on the level of operating profitability, these differences could mask the effect of disclosing backlog on the persistence of operating profitability. For instance, disclosers are older and in a more mature life cycle stage on average, and these firms typically have *more* persistent operating profitability (Dickinson 2011). In untabulated analyses, I find that simply controlling for the differential persistence of mature firms increases the significance of the differences in the persistence of operating profitability for disclosers and non-disclosers to conventional two-tailed levels in columns 2 and 3 (p-value = 0.181 in column 1 specification). Although I do not interact all matching controls with $RNOA_{it}$ in this table to avoid problems associated with multicollinearity, in untabulated analyses I find that including these controls strengthens inferences regarding the negative effects of disclosing backlog on the persistence of operating profitability.
[19] Inferences are unchanged if I exclude firm-years with average net operating assets less than $1 million to avoid a small denominator problem.

Overall, the results in Table 5 are consistent with the order backlog providing information that is useful to competitors of make-to-order firms. These results suggest that disclosing order backlog could impose proprietary costs on some firms.[20]

5. Additional analyses and limitations

5.1. Management forecasts and investors' expectations of future earnings

Although a unique characteristic of backlog information is that it is a mandatory quantitative forward-looking disclosure, management forecasts convey similar information.[21] This provides an opportunity to investigate how mandatory and voluntary disclosures interact to influence investors' forecasting and pricing decisions. On the one hand, because management forecasts are more salient and easier to process than the information in backlog disclosures, investors may not identify or process backlog in the presence of management forecasts (Hirshleifer and Teoh 2003). Thus, management forecasts could substitute for backlog disclosures. On the other hand, because managers likely use backlog when forecasting future performance, disclosing the dollar amount of outstanding order backlog could enhance the credibility of management forecasts by effectively presenting a more disaggregated forecast (Hirst et al. 2007).

I provide a preliminary examination of how management forecasts and backlog disclosures interact to influence investors' forecasting and pricing decisions. Specifically, I examine 1) whether disclosing backlog is associated with higher FERCs if managers provide a quantitative EPS forecast, and 2) whether investors place greater weight on managers' EPS forecasts in their

[20] The greater investment efficiency of disclosers could be attributable to greater competition rather than monitoring per se (Grenadier 2002). In other words, the monitors that result in higher investment efficiency could be competitors. To the extent competition reduces agency costs (i.e., competition serves as a disciplining mechanism), the conclusion that disclosing backlog has monitoring benefits and important real effects is unchanged.

[21] I find that the propensity to provide a management earnings or revenue forecast does not differ between disclosers and non-disclosers once year and industry are controlled for and therefore is unlikely to be a correlated omitted variable in my main analyses. Nonetheless, in untabulated analyses, I include an indicator variable for whether management provides an earnings or revenue forecast in the three months subsequent to the fiscal year end as an additional control; inferences are qualitatively unchanged.

valuation decisions when the firm also discloses backlog. Specifically, I use management EPS forecasts from I/B/E/S Guidance and estimate the following OLS regression:

$$Ret_{it} = \beta_0 + \beta_1 Earn_{it-1} + \beta_2 Earn_{it} + \beta_3 Earn_{it+1} + \beta_4 Ret_{it+1} + \beta_5 Earn_{it-1} \times Discloser_{it} + \beta_6 Earn_{it} \times Discloser_{it} + \beta_7 Earn_{it+1} \times Discloser_{it} + \beta_8 Ret_{it+1} \times Discloser_{it} + \beta_9 Discloser_{it} + \beta_{10} Forecast_{it} + \beta_{11} Forecast_{it} \times Discloser_{it} + e_{it} \quad (4)$$

I define $Forecast_{it}$ as management's most recent quantitative EPS forecast for fiscal year t + 1 provided in the three months subsequent to the end of fiscal year t, scaled by the firm's stock price three months after the end of fiscal year t – 1. I present the results of estimating equation 4 in Table 6. Amongst the firms that provide a quantitative EPS forecast in the full sample, I continue to find evidence that disclosing backlog is associated with significantly higher FERCs (column 1). In column 2, I find that the information in management forecasts is impounded into current period returns for disclosers but not non-disclosers. Specifically, while β_{10} is not significantly different from zero at conventional two-tailed levels, an F-test of the joint significance of (β_{10} + β_{11}) is significantly different from zero (p-value = 0.014). I find similar results for the matched sample.

Overall, these results suggest investors do not view management forecasts as a complete substitute for backlog disclosures and in fact disclosing the dollar amount of order backlog could improve the credibility of these forecasts. However, further research is required to fully explore these relations.

5.2. Supporting evidence of the usefulness of backlog information

Thus far, I find evidence of several differences in firm outcomes for firms that disclose order backlog relative to those that do not. I interpret these results to suggest that disclosing the dollar amount of order backlog provides information that is useful to various stakeholders and thus influences their decisions. One limitation of these results, however, is that I do not directly measure stakeholders' decisions. Moreover, although comparing firm outcomes of disclosers and non-disclosers is necessary to address the question of whether the disclosure is incrementally informative (because I cannot observe the amount of backlog for non-disclosers), differences between disclosers and non-disclosers raise concerns about unobservable omitted variables in my analyses. To provide support for my interpretation of the results, I conduct a number of additional analyses that examine the information content of the dollar amount of backlog amongst disclosers. I present the results of these analyses in the Appendix E.

5.2.1. Additional analyses for H1

In my primary analysis of the usefulness of backlog information for investors I find that disclosers have significantly higher FERCs than non-disclosers on average. Drawing on arguments from prior literature, I contend that this result is attributable to the fact that backlog provides information about future earnings that is not contained in current earnings (Lundholm and Myers 2002). I investigate the validity of this assumption by examining the extent to which changes in order backlog predict future earnings beyond the information contained in current earnings. Specifically, I estimate the following regression model using OLS:

$$E_{it+1} = \beta_0 + \beta_1 E_{it} + \beta_2 \Delta OB_{it} + e_{it+1} \tag{5}$$

I define E_{it+1} (E_{it}) as earnings before extraordinary items in fiscal year $t + 1$ (t) scaled by average total assets in fiscal year t and similarly define ΔOB_{it} as the change in order backlog from fiscal year $t – 1$ to t scaled by average total assets in fiscal year t.[22]

Consistent with the results that demonstrate a positive association between growth in backlog intensity and future sales growth, I find that changes in order backlog are significantly

[22] Although backlog has a stronger conceptual relation to sales and thus measuring changes in backlog relative to sales is perhaps a more natural choice to capture the information content of backlog, and is in fact the proxy I use in other analyses, I scale by average total assets in this analysis to maintain a consistent denominator in the regression model. Nonetheless, my inferences throughout the paper are robust to the use of different denominators.

positively associated with future earnings, holding constant current earnings. I also include year fixed effects and decompose current earnings into its cash flow and accrual components and continue to find that changes in order backlog have information content about future earnings beyond current earnings information. These results support investor's use of backlog information in revising their expectations of future performance.

I contend that because backlog provides information about future earnings beyond that in current period earnings news, disclosing this information changes investors' expectations of future earnings and is associated with a stronger correlation between future earnings and current returns. Because I can more directly observe analysts' expectations of future performance, I investigate whether analysts revise their forecasts in response to backlog information to provide further support for my interpretation of these results. Specifically, I estimate the following OLS regression:

$$AnalystRevision_{it}^{t+1} = \beta_0 + \beta_1 Surprise_{it} + \beta_2 \%\Delta Backlog_{it} + \Gamma Controls_{it} + \phi_t + e_{it} \qquad (6)$$

I calculate $AnalystRevision_{it}^{t+1}$ as the change in the most recent median consensus annual EPS (sales) forecast for fiscal year t + 1 from prior to the earnings announcement for fiscal year t to the first forecast provided within 15 days after the fiscal year t 10-K filing date, divided by the firm's stock price (market value of equity) at the end of fiscal year t (see Figure E.1 Appendix E for a timeline of variable measurement). I define $Surprise_{it}$ as the difference between actual annual EPS (sales) for fiscal year t and the most recent analyst consensus forecast provided within 30 days prior to the annual earnings announcement. Finally, I define $\%\Delta Backlog_{it}$ as the percentage change in backlog intensity (backlog divided by sales) and control for several forecast characteristics (e.g., age of the forecast before revision, standard deviation of consensus forecast).[23] To facilitate interpretation of the coefficients, I decile rank all independent variables and scale the rank to be between zero and one.

Consistent with backlog providing information that changes analysts' expectations of future performance, I find a significant positive association between growth in backlog intensity and analysts' forecast revisions. This relation is also economically significant; moving from the bottom to top decile in backlog growth is associated with an increase in the (scaled) consensus analyst EPS forecast of 0.005, which is less than the interquartile range of the distribution of analysts' EPS forecast revisions of 0.008 but much greater than the median revision (-0.0003). I find similar results for analysts' annual sales forecast revisions.

5.2.2. Additional analyses for H2

In developing my second hypothesis, I conjecture that because order backlog is informative about demand for the firm's product, disclosing this information could reduce information asymmetry about the firm's investment opportunities.[24] If this is an important mechanism in explaining the greater investment efficiency of disclosers, the investments of disclosers should be sensitive to changes in backlog, holding current investment levels constant. Moreover, if managers anticipate that their investment decisions will be evaluated using backlog information, I expect that this sensitivity should be stronger (weaker) for firms that have stronger (weaker)

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[23] I truncate 369 observations with growth in backlog intensity greater than 100% from the analyses that use $\%\Delta Backlog_{it}$ as an independent variable as these observations likely represent firm-years in which the firm is facing significant operational changes or difficulties. For instance, 167 of these observations experienced a loss in fiscal year *t* and the average (median) sales growth during the year is 1.74% (-3.01%) in this sample. Thus, I expect that backlog growth is less likely to be indicative of demand growth and more likely to be attributable to performance difficulties for these firms, which would decrease the power of the empirical tests. Nonetheless, inferences are qualitatively unchanged if I include these observations.

[24] In untabulated analyses, I find that growth in backlog intensity is significantly positively associated with changes in Tobin's Q, a measure of investment opportunities, supporting the conjecture that backlog is informative about a firm's investment opportunities.

monitoring (e.g., a higher proportion of institutional ownership). I test this implication using the following OLS regression:

$$Capex_{it+1} = \beta_0 + \beta_1 Capex_{it} + \beta_2 \%\Delta Backlog_{it} + \beta_3 \%\Delta Backlog_{it} \times Monitor_{it} + \beta_4\, Monitor_{it} + \Gamma Controls_{it} + \gamma_j + \phi_t + e_{it+1} \quad (7)$$

I define $Capex_{it+1}$ and $\%\Delta Backlog_{it}$ as above. To facilitate interpretation of the coefficients, I decile rank backlog growth and scale the rank to be between zero and one. $Monitor_{it}$ equals either $InstOwn_{it}$, which measures the proportion of total common shares held by institutional owners at the end of fiscal year t, or E_Index_{it}, which is the entrenchment index described in Bebchuk et al. (2009). The entrenchment index ranges from 0 to 6 depending on whether the firm has one of six governance provisions that are expected to be negatively associated with governance quality (see Appendix D for the specific provisions).[25] I obtain data on institutional ownership from Thomson Reuters Institutional Holdings (13f) and data on governance provisions from Risk Metrics. If managers expect monitors to use backlog information in evaluating the quality of investment decisions, I expect $\beta_3 > (<) 0$ when $Monitor_{it}$ equals $InstOwn_{it}$ (E_Index_{it}).

Consistent with backlog growth being informative about changes in demand, holding current investment levels constant, I find a significant positive association between backlog growth and future capital expenditures ($\beta_2 > 0$). The results also illustrate that the sensitivity of future investment to current changes in backlog is higher when the firm has greater institutional ownership ($\beta_3 > 0$), although this result is not significant at conventional two-tailed levels (two-tailed p-value = 0.116). Due to data availability, the sample size is much smaller when using the entrenchment index to proxy for monitoring. Nonetheless, I find that the investment decisions of

[25] Although the entrenchment index is a measure of governance quality rather than monitoring intensity per se, I argue that because it captures governance provisions that limit the ability of monitors to take actions that discipline managers' behavior, it captures the kind of monitoring discipline I am interested in.

firms with higher values of the entrenchment index (i.e., with weaker monitoring) are less sensitive to backlog growth.

5.2.3. Additional analyses for H3

To examine whether backlog information is useful for competitors in making product market and investment decisions, I compare the persistence of operating profitability for a matched sample of disclosers and non-disclosers. This empirical approach, however, does not examine *how* competitors use backlog information, which could provide further support for the argument that backlog information is useful to competitors. However, there are at least two reasons why conducting such an empirical test would be difficult for a broad cross-section of firms and industries. First, the strategic response to the signal backlog provides can differ across industries or firms (e.g., pricing or production changes, entry or exit decisions), whereas measuring the persistence of operating profitability provides a measure of competitive intensity that should apply broadly in the cross-section. Thus, any examination of a specific reaction would likely result in a low powered test. Second, the argument that order backlog information is useful for competitors does not depend on competitors taking any action. Rather, the threat of competition is sufficient to induce firms to act in a way that reflects a perception of the usefulness of backlog information for competitors (Grenadier 2002).

Nonetheless, I next conduct an exploratory analysis in which I consider whether changes in backlog intensity are associated with the persistence of operating profitability and if this association varies across industries with different levels of sales concentration. In particular, I estimate the following regression model using OLS:

$$RNOA_{it+1} = \beta_0 + \beta_1 RNOA_{it} + \beta_2 RNOA_{it} \times \%\Delta Backlog_{it} + \beta_3 \%\Delta Backlog_{it} + e_{it+1} \qquad (8)$$

All variables are as defined in previous analyses. To facilitate interpretation of the coefficients, I decile rank $\%\Delta Backlog_{it}$ and scale the rank to be between zero and one. Consistent with earlier analyses, changes in backlog intensity are positively associated with future profitability ($\beta_3 > 0$). I also find a significant positive coefficient on β_2, which suggests that backlog can provide information about the persistence of changes in demand. This effect is economically significant—the persistence of operating profitability is 11.1% higher in the top decile of backlog intensity growth than in the bottom decile (the coefficient increases from 0.659 to 0.732).

I next estimate equation 8 separately for firms in industries with different levels of average sales concentration during my sample period (i.e., the Herfindahl-Hirschman Index). Specifically, I calculate the average concentration ratio for each industry and split the sample into two groups on the basis of the median ratio in the full sample (see Appendix C for the average ratio in each industry). I find that the positive association between the persistence of operating profitability and the growth in backlog intensity exists only in industries with relatively lower sales concentration. This result could indicate that firms in industries with high levels of concentration face greater difficulties in protecting the rents associated with changes in demand.

5.3. Limitations

Although the backlog disclosure setting provides an opportunity to examine the implications of disclosing order backlog per se, identifying these effects involves certain empirical challenges. Most notably, because firms' backlog disclosure policies are not exogenously determined, it is possible that systematic differences between disclosers and non-disclosers lead to omitted variables. Several elements of my empirical design are intended to mitigate this concern. First, I find that my results are robust to the use of a matched sample of firms with similar characteristics but different disclosure policies. Second, I examine how disclosing backlog is associated with the implied decisions of several stakeholder groups, which provides a broad assessment of the usefulness of these disclosures and reduces the likelihood that a single omitted variable explains the entire set of results. Third, I find that my results are predictably concentrated amongst firms for which backlog is predicted to be a more relevant signal. Finally, results of analyses amongst a sample of disclosers are consistent with backlog providing information that is consistent with *how* stakeholders might use these disclosures in their decision-making processes, supporting my inferences about *whether* stakeholders find backlog disclosures useful on average.

One potential alternative interpretation of my main results is that I do not adequately control for differences in demand uncertainty between disclosers and non-disclosers. To examine the importance of this concern, I test whether disclosers face significantly less uncertainty about demand by comparing the specificity of managers' forecasts for disclosers and non-disclosers. For firms in which managers provide an EPS forecast in the full sample (i.e., those firms in Table 6, columns 1-2), managers of firms that disclose backlog are no more likely to provide a point versus a range forecast than managers of firms that do not disclose backlog (not tabulated). To the extent fundamental uncertainty influences a manager's choice of forecast type, this mitigates concerns that differences in demand uncertainty between disclosers and non-disclosers explain my results. Nonetheless, despite the features of my empirical design and other descriptive evidence, I acknowledge there are limitations and alternative interpretations of the results that cannot be fully ruled out.

Other aspects of this study could adversely affect the generalizability of the results. First, although backlog is a mandatory disclosure, there is no evidence that the regulatory costs of non-compliance are particularly high. Consequently, assuming that my matched sample controls for observable differences between disclosers and non-disclosers, differences in discloser status could reflect managerial discretion. The impact of managerial discretion over the disclosure outcome would imply that disclosers are the firms that perceive greater net benefits from disclosing backlog. If such discretion is a significant determinant of firms' backlog disclosure policies during my sample period, this would bias my analyses in favor of (against) documenting benefits (costs) of disclosing backlog. Nonetheless, such discretion potentially creates a selection on unobservables problem that could reduce the generalizability of my findings but should not change my inferences for my sample firms.

Second, I focus on a subset of firms that have order backlog, thus excluding some firms that disclose order backlog. I exclude these firms as it is more difficult to understand the reasons for non-disclosure in other industries and because pooling different sectors (i.e., manufacturing and non-manufacturing) would introduce more differences into the sample, raising additional concerns about omitted variables. However, conceptual differences in backlog across sectors could lead to different benefits and costs associated with disclosing backlog. Nonetheless, because of the history of reporting backlog in the manufacturing industry, understanding whether backlog provides useful information to stakeholders of firms in these industries represents an important first step.

6. Conclusion and future research

I provide evidence that the dollar amount of order backlog provides useful information for stakeholders such that there are important implications associated with disclosing this information. Disclosers have significantly higher FERCs (i.e., greater price informativeness), greater investment efficiency, and less persistent operating profitability. These findings and those of additional analyses suggest that backlog can be informative not just for valuation purposes, but also for monitoring managers' investment decisions and for competitors in making product market and investment decisions. Consistent with concerns about the relevance of backlog disclosures for all firms (SEC 2016), I find that the consequences of disclosing backlog are concentrated in the subsample of firms for which backlog is a more relevant signal of demand (i.e., those that adhere more closely to a make-to-order business model). Thus, although disclosing the dollar amount of order backlog can provide capital market and monitoring benefits, it could also impose proprietary costs on some firms. Finally, I present preliminary evidence that disclosing order backlog has some incremental usefulness for investors' forecasting and valuation decisions beyond management forecasts, as well as increasing the credibility of these forecasts.

There are several opportunities for future research to further explore the insights of this study, as well as extend the results into other settings. First, there is cross-sectional variation in the additional information firms provide in their order backlog disclosures (e.g., fulfillment periods). This discretionary, primarily qualitative, component of order backlog disclosures could impact the usefulness of the disclosure. Second, although I use firm outcomes to infer whether stakeholders use backlog information, future research could further explore the specific mechanisms through which these outcomes occur. For instance, how do order backlog disclosures affect competitors' product market and investment decisions? Third, given the evidence that backlog information appears to influence stakeholders' decisions, an important question is whether managers utilize their discretion to misreport the dollar amount of order backlog. Finally, future research could further examine how public disclosure of this information regulates other decisions. For instance, do firms that disclose order backlog have timelier inventory writedowns and/or goodwill impairments?

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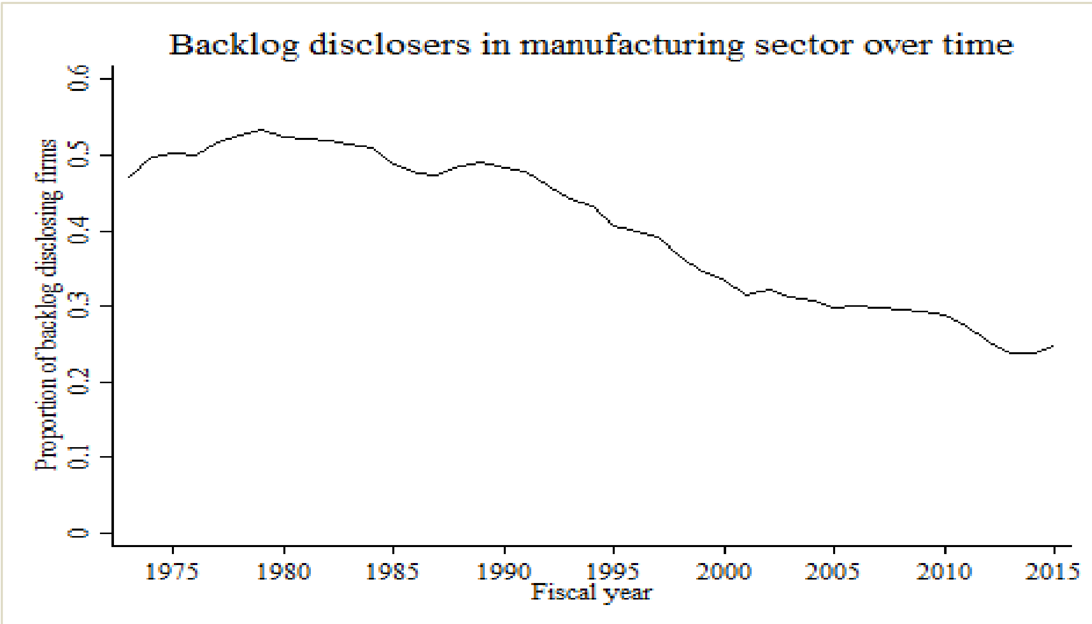
Figure 1: Trends in backlog reporting over time



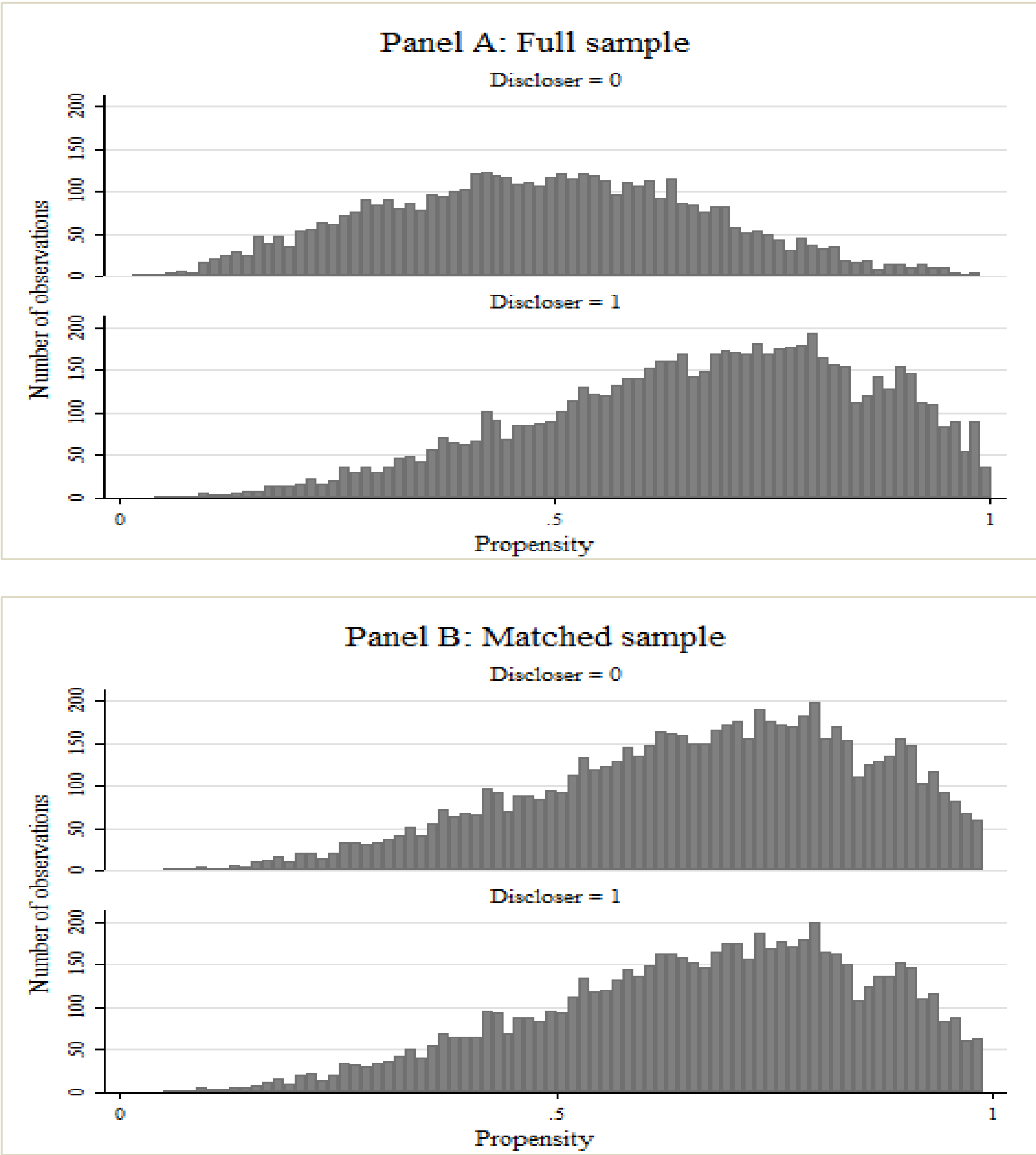
This figure plots the average proportion of firms that disclose backlog within the manufacturing sector (NAICS 2-digit codes 31-33). In this figure I include all firms on Compustat with non-missing assets and subsectors (defined by NAICS 3-digit codes) in which there are at least 100 firms that disclose backlog between 1973-2015.

Figure 2: Transition matrix for disclosure outcome

		$Discloser_{it}$ 0	$Discloser_{it}$ 1
$Discloser_{it-1}$	0	4,579	168
	1	162	6,771

This figure depicts the transition of observations in the full sample between discloser (*Discloser* = 1) and non-discloser (*Discloser* = 0) status from fiscal year $t - 1$ to fiscal year t. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year t and zero otherwise.

Figure 3: Distribution of propensity scores by discloser status



This figure plots the distribution of the propensity score (*Propensity*$_{it}$), which equals the estimated probability that a given firm-year discloses order backlog from the propensity score model in Table 1, separately for disclosers (*Discloser*$_{it}$ = 1) and non-disclosers (*Discloser*$_{it}$ = 0). *Discloser*$_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year *t* and zero otherwise. Panel A presents the distribution of the full sample before matching and Panel B presents the distribution after implementing the matching procedure described in Appendix B.

Table 1: Propensity score model

	Dependent variable: $Discloser_{it}$	
	(1)	(2)
VARIABLES	Coefficient estimates	Marginal effects
$FinishedGoods_{it}$	-1.066***	-0.251***
	(-4.43)	(-4.43)
$LnR\&D_{it}$	-0.713**	-0.168**
	(-2.26)	(-2.26)
$GrossMargin_{it}$	-2.391***	-0.562***
	(-5.61)	(-5.63)
$SalesVolatility_{it}$	-1.785	-0.419
	(-1.47)	(-1.47)
$\lvert Accruals_{it}\rvert$	-2.064***	-0.485***
	(-5.82)	(-5.81)
$GovCustomer_{it}$	0.990***	0.233***
	(4.42)	(4.46)
$MajorCustomer_{it}$	-0.150	-0.035
	(-1.47)	(-1.47)
$Advertising_{it}$	-0.201*	-0.047*
	(-1.70)	(-1.70)
$GrowthFirm_{it}$	0.242**	0.057**
	(2.47)	(2.48)
$MatureFirm_{it}$	0.213**	0.050**
	(2.05)	(2.05)
$ShakeoutFirm_{it}$	0.240**	0.056**
	(2.19)	(2.19)
$DeclineFirm_{it}$	-0.069	-0.016
	(-0.56)	(-0.56)
$PeerBacklog_{it}$	1.102***	0.259***
	(3.03)	(3.02)
$Size_{it}$	0.028	0.007
	(0.71)	(0.72)
BM_{it}	0.191	0.045
	(1.55)	(1.55)
$Leverage_{it}$	0.238	0.056
	(0.66)	(0.66)
$MajorExchange_{it}$	0.152	0.036
	(0.92)	(0.92)
DQ_{it}	2.291***	0.539***
	(3.78)	(3.77)
$FirmAge_{it}$	0.322***	0.076***
	(2.87)	(2.87)
$NewFirm_{i}$	-0.523***	-0.123***
	(-2.59)	(-2.60)
Observations	11,680	
Pseudo R^2	0.145	
Area under ROC Curve	0.752	

This table presents the results of estimating a logit regression in which the dependent variable ($Discloser_{it}$) is an indicator variable equal to one if the firm discloses order backlog in fiscal year *t* and zero otherwise.

$FinishedGoods_{it}$ equals the proportion of total inventory held as finished goods, $LnR\&D_{it}$ equals the natural log of one plus R&D expenditures divided by sales. $GrossMargin_{it}$ represents the firm's gross margin ratio. $SalesVolatility_{it}$ is the quarterly sales volatility over the prior two years. $|Accruals_{it}|$ measures the absolute value of accruals scaled by total assets. $GovCustomer_{it}$ is an indicator variable equal to one if the firm reports a government agency as a major customer. $MajorCustomer_{it}$ is an indicator variable equal to one if the firm reports a major corporate customer. $Advertising_{it}$ is an indicator variable equal to one if the firm reports non-zero advertising expense, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, and $DeclineFirm_{it}$ are indicator variables equal to one if the cash flows of the firm suggest the firm is in a growth, mature, shakeout or decline stage following Dickinson (2011). $PeerBacklog_{it}$ is calculated as the aggregate backlog of industry peers scaled by the aggregate sales of industry peers. $Size_{it}$ measures the natural log of market value of equity at the end of the fiscal year. BM_{it} is the firm's book-to-market ratio at the end of the fiscal year. $Leverage_{it}$ equals the firm's market leverage ratio. $MajorExchange_{it}$ is an indicator variable equal to one if the firm is listed on the NYSE, AMEX, or NASDAQ. DQ_{it} is a balance sheet disaggregation-based measure of disclosure quality, calculated following Chen et al. (2015). $FirmAge_{it}$ is the natural log of one plus the number of years since the firm's first fiscal year of available accounting data. $NewFirm_{i}$ is an indicator variable equal to one if the first fiscal year of available accounting data for the firm is after 1996. All continuous variables (except DQ_{it}, which is bound by 0 and 1, and $PeerBacklog_{it}$) are winsorized at the 1st and 99th percentiles. The model includes industry and year fixed effects and standard errors are clustered by firm. Industries are defined using 4-digit NAICS codes. Appendix D provides complete variable definitions including data items. Z-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table 2: Descriptive statistics

Panel A: Full sample

	N	Mean	Std Dev	25th %	Median	75th %
$Discloser_{it}$	11,680	0.594	0.491	0.000	1.000	1.000
Propensity score model independent variables						
$FinishedGoods_{it}$	11,680	0.345	0.260	0.139	0.310	0.516
$LnR\&D_{it}$	11,680	0.004	0.099	0.000	0.000	0.001
$GrossMargin_{it}$	11,680	0.408	0.157	0.297	0.396	0.517
$SalesVolatility_{it}$	11,680	0.043	0.037	0.019	0.032	0.054
$GovCustomer_{it}$	11,680	0.084	0.277	0.000	0.000	0.000
$MajorCustomer_{it}$	11,680	0.479	0.500	0.000	0.000	1.000
$Advertising_{it}$	11,680	0.325	0.468	0.000	0.000	1.000
$\|Accruals_{it}\|$	11,680	0.080	0.079	0.028	0.058	0.105
$IntroFirm_{it}$	11,680	0.117	0.321	0.000	0.000	0.000
$GrowthFirm_{it}$	11,680	0.305	0.460	0.000	0.000	1.000
$MatureFirm_{it}$	11,680	0.407	0.491	0.000	0.000	1.000
$ShakeoutFirm_{it}$	11,680	0.116	0.320	0.000	0.000	0.000
$DeclineFirm_{it}$	11,680	0.056	0.229	0.000	0.000	0.000
$PeerBacklog_{it}$	11,680	0.293	0.383	0.081	0.139	0.393
$Size_{it}$	11,680	5.628	2.078	4.028	5.606	7.076
BM_{it}	11,680	0.620	0.451	0.319	0.507	0.790
$Leverage_{it}$	11,680	0.148	0.178	0.002	0.081	0.229
$MajorExchange_{it}$	11,680	0.864	0.343	1.000	1.000	1.000
DQ_{it}	11,680	0.871	0.102	0.820	0.890	0.951
$FirmAge_{it}$	11,680	2.841	0.697	2.303	2.833	3.401
$NewFirm_{i}$	11,680	0.150	0.357	0.000	0.000	0.000
Dependent variables and other control variables						
$Earn_{it-1}$	11,680	0.007	0.135	-0.004	0.036	0.063
$Earn_{it}$	11,680	0.006	0.136	-0.011	0.037	0.066
$Earn_{it+1}$	11,680	0.013	0.140	-0.022	0.036	0.075
Ret_{it}	11,680	0.133	0.625	-0.273	0.025	0.376
Ret_{it+1}	11,680	0.135	0.644	-0.271	0.022	0.370
$Capex_{it+1}$	11,680	0.049	0.057	0.018	0.032	0.057
$TobinsQ_{it}$	11,680	1.842	1.135	1.135	1.516	2.141
PPE_{it}	11,680	0.405	0.260	0.211	0.346	0.534
$CFOSale_{it}$	11,680	0.067	0.122	0.017	0.078	0.130
$Cash_{it}$	11,680	0.199	0.176	0.048	0.154	0.310
$Dividend_{it}$	11,680	0.287	0.452	0.000	0.000	1.000
$Loss_{it}$	11,680	0.282	0.450	0.000	0.000	1.000
$RNOA_{it}$	11,680	0.122	0.271	0.021	0.133	0.250
$RNOA_{it+1}$	11,680	0.101	0.272	0.000	0.121	0.234

Table 2, continued.

Panel B: Matched sample

	N	Mean	Std Dev	25th %	Median	75th %
$Discloser_{it}$	13,742	0.500	0.500	0.000	0.500	1.000
Propensity score model independent variables						
$FinishedGoods_{it}$	13,742	0.308	0.248	0.099	0.274	0.464
$LnR\&D_{it}$	13,742	0.003	0.034	0.000	0.000	0.001
$GrossMargin_{it}$	13,742	0.375	0.154	0.267	0.365	0.478
$SalesVolatility_{it}$	13,742	0.042	0.034	0.019	0.033	0.054
$GovCustomer_{it}$	13,742	0.121	0.326	0.000	0.000	0.000
$MajorCustomer_{it}$	13,742	0.490	0.500	0.000	0.000	1.000
$Advertising_{it}$	13,742	0.281	0.450	0.000	0.000	1.000
$\|Accruals_{it}\|$	13,742	0.074	0.073	0.026	0.053	0.096
$IntroFirm_{it}$	13,742	0.110	0.313	0.000	0.000	0.000
$GrowthFirm_{it}$	13,742	0.308	0.462	0.000	0.000	1.000
$MatureFirm_{it}$	13,742	0.416	0.493	0.000	0.000	1.000
$ShakeoutFirm_{it}$	13,742	0.113	0.317	0.000	0.000	0.000
$DeclineFirm_{it}$	13,742	0.052	0.223	0.000	0.000	0.000
$PeerBacklog_{it}$	13,742	0.301	0.347	0.094	0.171	0.393
$Size_{it}$	13,742	5.471	2.119	3.849	5.399	6.946
BM_{it}	13,742	0.655	0.467	0.332	0.539	0.833
$Leverage_{it}$	13,742	0.146	0.172	0.002	0.083	0.226
$MajorExchange_{it}$	13,742	0.864	0.343	1.000	1.000	1.000
DQ_{it}	13,742	0.873	0.095	0.827	0.888	0.946
$FirmAge_{it}$	13,742	2.917	0.692	2.398	2.944	3.466
$NewFirm_{i}$	13,742	0.106	0.308	0.000	0.000	0.000
Dependent variables and other control variables						
$Earn_{it-1}$	13,742	0.010	0.134	-0.001	0.038	0.066
$Earn_{it}$	13,742	0.012	0.134	-0.007	0.041	0.068
$Earn_{it+1}$	13,742	0.016	0.144	-0.018	0.038	0.079
Ret_{it}	13,742	0.128	0.618	-0.268	0.021	0.376
Ret_{it+1}	13,742	0.144	0.636	-0.251	0.032	0.382
$Capex_{it+1}$	13,742	0.047	0.055	0.018	0.031	0.055
$TobinsQ_{it}$	13,742	1.765	1.057	1.095	1.465	2.058
PPE_{it}	13,742	0.416	0.255	0.228	0.358	0.541
$CFOSale_{it}$	13,742	0.062	0.118	0.018	0.073	0.121
$Cash_{it}$	13,742	0.188	0.169	0.046	0.142	0.293
$Dividend_{it}$	13,742	0.304	0.460	0.000	0.000	1.000
$Loss_{it}$	13,742	0.267	0.442	0.000	0.000	1.000
$RNOA_{it}$	13,742	0.123	0.259	0.028	0.134	0.247
$RNOA_{it+1}$	13,742	0.104	0.262	0.007	0.122	0.233

Table 2, continued.

Panel C: Comparison of disclosers and non-disclosers

	Full sample			Matched sample		
	$Discloser_{it}$ =			$Discloser_{it}$ =		
	0 (N=4,741)	1 (N=6,939)	Std. Diff. in Means	0 (N=6,871)	1 (N=6,871)	Std. Diff. in Means
$FinishedGoods_{it}$	0.406	0.303***	0.418	0.310	0.305	0.022
$LnR\&D_{it}$	0.007	0.003	0.099	0.003	0.003	0.006
$GrossMargin_{it}$	0.447	0.382***	0.453	0.366	0.383	-0.117
$SalesVolatility_{it}$	0.045	0.041***	0.117	0.043	0.041	0.047
$GovCustomer_{it}$	0.034	0.117***	-0.258	0.132	0.111	0.066
$MajorCustomer_{it}$	0.497	0.467	0.059	0.514	0.467	0.094
$Advertising_{it}$	0.404	0.271***	0.299	0.289	0.274	0.035
$\|Accruals_{it}\|$	0.091	0.073***	0.237	0.074	0.074	0.004
$IntroFirm_{it}$	0.130	0.108**	0.069	0.111	0.109	0.008
$GrowthFirm_{it}$	0.306	0.304	0.006	0.313	0.304	0.021
$MatureFirm_{it}$	0.384	0.422**	-0.077	0.412	0.420	-0.017
$ShakeoutFirm_{it}$	0.115	0.117	-0.006	0.109	0.118	-0.028
$DeclineFirm_{it}$	0.065	0.049***	0.071	0.055	0.050	0.023
$PeerBacklog_{it}$	0.225	0.340***	-0.257	0.283	0.319	-0.080
$Size_{it}$	5.673	5.597	0.037	5.364	5.579	-0.104
BM_{it}	0.585	0.645***	-0.134	0.663	0.646	0.037
$Leverage_{it}$	0.145	0.150	-0.028	0.142	0.149	-0.040
$MajorExchange_{it}$	0.850	0.873	-0.070	0.855	0.872	-0.052
DQ_{it}	0.868	0.872	-0.038	0.874	0.872	0.017
$FirmAge_{it}$	2.693	2.943***	-0.368	2.900	2.934	-0.050
$NewFirm_{i}$	0.217	0.104***	0.369	0.108	0.105	0.008
Dependent variables and other control variables						
$Earn_{it-1}$	-0.004	0.014***	-0.137	0.007	0.014	-0.047
$Earn_{it}$	-0.006	0.014***	-0.153	0.010	0.013	-0.024
$Earn_{it+1}$	0.001	0.022***	-0.155	0.011	0.021*	-0.078
Ret_{it}	0.123	0.139	-0.028	0.118	0.138*	-0.033
Ret_{it+1}	0.128	0.139	-0.017	0.149	0.139	0.016
$Capex_{it+1}$	0.055	0.045***	0.199	0.050	0.045	0.083
$TobinsQ_{it}$	1.998	1.735***	0.264	1.795	1.736	0.059
PPE_{it}	0.398	0.409	-0.047	0.422	0.410	0.050
$CFOSale_{it}$	0.065	0.069	-0.036	0.056	0.069**	-0.121
$Cash_{it}$	0.219	0.186***	0.192	0.189	0.187	0.012
$Dividend_{it}$	0.238	0.320***	-0.176	0.291	0.318	-0.058
$Loss_{it}$	0.334	0.246***	0.205	0.286	0.248**	0.089
$RNOA_{it}$	0.101	0.137***	-0.142	0.110	0.136**	-0.105
$RNOA_{it+1}$	0.078	0.117***	-0.160	0.091	0.117*	-0.103

This table presents summary statistics for the full sample (matched sample) in Panel A (B). In Panel C I compare the mean values of various firm characteristics for disclosers and non-disclosers before and after matching. Std. Diff. in Means represents the standardized difference in means, calculated as the difference in the average values for disclosers and non-disclosers, scaled by the standard deviation of the full sample of disclosers. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year t and zero otherwise. $FinishedGoods_{it}$ equals the proportion of total inventory held as finished goods. $LnR\&D_{it}$ equals the natural log of one plus R&D

expenditures divided by sales. $GrossMargin_{it}$ represents the firm's gross margin ratio. $SalesVolatility_{it}$ is the quarterly sales volatility over the prior two years. $|Accruals_{it}|$ measures the absolute value of accruals scaled by total assets. $GovCustomer_{it}$ is an indicator variable equal to one if the firm reports a government agency as a major customer. $MajorCustomer_{it}$ is an indicator variable equal to one if the firm reports a major corporate customer. $Advertising_{it}$ is an indicator variable equal to one if the firm reports non-zero advertising expense, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, and $DeclineFirm_{it}$ are indicator variables equal to one if the cash flows of the firm suggest the firm is in a growth, mature, shakeout or decline stage following Dickinson (2011). $PeerBacklog_{it}$ is calculated as the aggregate backlog of industry peers scaled by the aggregate sales of industry peers. $Size_{it}$ measures the natural log of market value of equity at the end of the fiscal year. BM_{it} is the firm's book-to-market ratio at the end of the fiscal year. $Leverage_{it}$ equals the firm's market leverage ratio. $MajorExchange_{it}$ is an indicator variable equal to one if the firm is listed on the NYSE, AMEX, or NASDAQ. DQ_{it} is a balance sheet disaggregation-based measure of disclosure quality, calculated following Chen et al. (2015). $FirmAge_{it}$ is the natural log of one plus the number of years since the firm's first fiscal year of available accounting data. $NewFirm_{i}$ is an indicator variable equal to one if the first fiscal year of available accounting data for the firm is after 1996. $Propensity_{it}$ is the propensity score, which represents the predicted value of disclosure from the model in Table 1. $Earn_{in}$ is calculated as earnings before extraordinary items in fiscal year n divided by market value of equity three months after the end of fiscal year t – 1. Ret_{in} measures the twelve-month buy-and-hold return beginning three months after the end of fiscal year n – 1. $Capex_{it+1}$ equals the ratio of capital expenditures in fiscal year t + 1 to sales in fiscal year t. $TobinsQ_{it}$ is Tobin's Q at the end of fiscal year t, which measures the ratio of the market value of assets to the book value of assets. PPE_{it} is property, plant, and equipment scaled by total assets. $CFOSale_{it}$ equals the ratio of operating cash flows to sales. $Cash_{it}$ equals the ratio of cash holdings to total assets. $Dividend_{it}$ is an indicator variable equal to one if the firm paid a dividend. $Loss_{it}$ is an indicator variable equal to one if the firm reports a loss in earnings before extraordinary items. $RNOA_{it}$ is calculated as operating income after depreciation divided by average net operating assets in year t. Appendix D provides complete variable definitions including data items. In Panel B, the differences in the average variable values are calculated after correcting for cross-sectional and time-series correlation. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (two-tailed).

Table 3: Forward earnings response coefficients
Panel A: Test of hypothesis 1

	Full sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}
$Earn_{it-1}$	-0.940***	-1.008***	-0.702***	-0.790***	-0.837***	-0.800***	-0.597***	-0.547***
	(-6.30)	(-5.95)	(-4.03)	(-9.16)	(-5.79)	(-4.37)	(-3.91)	(-3.88)
$Earn_{it}$	0.544***	0.581***	0.170	0.577***	0.563***	0.593***	-0.061	0.627***
	(3.93)	(4.39)	(1.20)	(6.16)	(3.60)	(3.05)	(-0.22)	(3.94)
$Earn_{it+1}$	1.510***	1.336***	1.657***	0.971***	1.434***	1.260***	1.646***	0.878***
	(8.67)	(8.00)	(6.73)	(9.98)	(8.73)	(7.73)	(4.66)	(6.37)
Ret_{it+1}	-0.201***	-0.203***	-0.212***	-0.116***	-0.205***	-0.211***	-0.266***	-0.122***
	(-4.32)	(-4.10)	(-3.47)	(-8.27)	(-3.89)	(-3.38)	(-2.82)	(-4.22)
$Earn_{it-1} \times Discloser_{it}$		0.118	0.029	0.027		-0.092	-0.078	-0.188
		(1.28)	(0.31)	(0.24)		(-0.65)	(-0.62)	(-1.24)
$Earn_{it} \times Discloser_{it}$		-0.058	-0.063	0.011		-0.074	0.026	-0.047
		(-0.49)	(-1.25)	(0.10)		(-0.50)	(0.18)	(-0.29)
$Earn_{it+1} \times Discloser_{it}$		0.311***	0.173**	0.236*		0.400***	0.171	0.377**
		(2.77)	(2.26)	(1.84)		(2.78)	(1.45)	(2.38)
$Ret_{it+1} \times Discloser_{it}$		0.004	0.011	-0.000		0.011	0.037	0.008
		(0.23)	(0.83)	(-0.01)		(0.35)	(1.09)	(0.26)
$Discloser_{it}$		-0.011	-0.011	-0.010		-0.000	-0.015	0.003
		(-0.76)	(-1.30)	(-1.01)		(-0.02)	(-1.11)	(0.17)
Intercept	0.143***	0.148**	0.503***	0.221***	0.137***	0.136**	0.531***	0.103
	(2.70)	(2.58)	(9.86)	(2.68)	(2.65)	(2.53)	(8.94)	(0.78)
F-test [($Earn_{it+1} \times Discloser_{it}$) + ($Ret_{it+1} \times Discloser_{it}$ = 0)]		**7.61*** **	**5.88** **	**3.62***		**10.27*** **	**4.23** **	**6.99*** **
FERC controls	No	No	Yes	Yes	No	No	Yes	Yes
Matching controls	No	No	No	Yes	No	No	No	Yes
Fixed effects	No	No	No	I,Y	No	No	No	I,Y
Standard error clustering	F,Y	F,Y	F,Y	F	F,Y	F,Y	F,Y	F
Observations	11,680	11,680	11,680	11,680	13,742	13,742	13,742	13,742
R^2	0.164	0.165	0.566	0.315	0.159	0.161	0.562	0.304

Table 3, continued.
Panel B: Cross-sectional test

	Full sample				Matched sample			
	MTS_{it} = 0		MTS_{it} = 1		MTS_{it} = 0		MTS_{it} = 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}
$Earn_{it-1}$	-1.076***	-0.482**	-0.854***	-0.695***	-0.725***	-0.254	-1.321***	-1.328***
	(-5.09)	(-2.54)	(-4.26)	(-2.76)	(-3.41)	(-1.62)	(-3.47)	(-4.28)
$Earn_{it}$	0.588***	0.115	0.582***	0.370*	0.506**	-0.142	0.937**	0.613
	(3.83)	(0.64)	(3.03)	(1.79)	(2.36)	(-0.68)	(2.37)	(1.61)
$Earn_{it+1}$	1.328***	1.117***	1.345***	1.163***	1.214***	1.071***	1.650***	1.533***
	(8.03)	(5.84)	(5.51)	(4.40)	(6.19)	(4.65)	(4.91)	(5.37)
Ret_{it+1}	-0.203***	-0.166***	-0.203***	-0.137***	-0.220***	-0.241***	-0.184***	-0.148***
	(-4.17)	(-6.12)	(-3.43)	(-3.21)	(-3.13)	(-5.69)	(-2.83)	(-2.59)
$Earn_{it-1} \times Discloser_{it}$	0.174	-0.052	0.032	-0.174	-0.181	-0.190*	0.499	0.188
	(1.25)	(-0.52)	(0.16)	(-1.28)	(-1.02)	(-1.82)	(1.48)	(1.02)
$Earn_{it} \times Discloser_{it}$	-0.125	-0.087	0.164	0.078	-0.048	0.009	-0.191	-0.121
	(-0.74)	(-0.85)	(0.86)	(0.67)	(-0.26)	(0.07)	(-0.46)	(-0.52)
$Earn_{it+1} \times Discloser_{it}$	0.378**	0.197*	0.060	-0.006	0.509***	0.222**	-0.245	-0.023
	(2.44)	(1.94)	(0.25)	(-0.05)	(2.59)	(2.05)	(-0.64)	(-0.14)
$Ret_{it+1} \times Discloser_{it}$	-0.008	-0.006	0.060	0.041*	0.009	0.033	0.041	0.054*
	(-0.58)	(-0.44)	(1.42)	(1.76)	(0.20)	(1.37)	(0.86)	(1.75)
$Discloser_{it}$	-0.013	-0.011	-0.012	-0.009	-0.003	-0.015	0.014	-0.012
	(-0.72)	(-1.08)	(-0.51)	(-0.49)	(-0.20)	(-0.96)	(0.38)	(-0.62)
Intercept	0.152**	0.029	0.138**	0.135	0.141**	0.131	0.113**	0.063
	(2.51)	(0.30)	(2.41)	(1.08)	(2.42)	(1.02)	(2.00)	(0.42)
F-test [($Earn_{it+1} \times Discloser_{it}$) + ($Ret_{it+1} \times Discloser_{it}$ = 0)]	**5.70****	**3.78***	**0.25**	**0.07**	**9.73*****	**6.49****	**0.30**	**0.04**
FERC controls	No	Yes	No	Yes	No	Yes	No	Yes
Matching controls	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	No	I, Y	No	I, Y	No	I, Y	No	I, Y
Standard error clustering	F, Y	F	F, Y	F	F, Y	F	F, Y	F
Observations	8,603	8,603	3,077	3,077	10,759	10,759	2,983	2,983
R^2	0.167	0.677	0.162	0.672	0.158	0.676	0.192	0.691

This table presents the results of estimating equation 1 and variations of this model. Ret_{in} measures the twelve-month buy-and-hold return beginning three months after the end of fiscal year $n - 1$. $Earn_{in}$ is calculated as earnings before extraordinary items in fiscal year n divided by market value of equity three months after the end of fiscal year $t - 1$. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year t and zero otherwise. Panel A presents the primary tests of my hypotheses and Panel B presents the results of estimating the main model (without controls) for firms that follow different business models (MTS_{it}). Specifically, firms are classified as following a make-to-stock business model (MTS_{it} = 1) if the proportion of total inventory held as finished goods ($FinishedGoods_{it}$) is greater than 0.50. FERC controls include $Loss_{it}$, $Beta_{it}$, $Coverage_{it}$, $Size_{it}$, BM_{it}, and an indicator variable equal to one if Ret_{it} is less than zero, and are included as main effects and interacted with $Earn_{it-1}$, $Earn_{it}$, $Earn_{it+1}$ and Ret_{it+1} when their inclusion is noted. Matching controls include $FinishedGoods_{it}$, $GrossMargin_{it}$, $|Accruals_{it}|$, $GovCustomer_{it}$, $MajorCustomer_{it}$, $Advertising_{it}$, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, $DeclineFirm_{it}$, $PeerBacklog_{it}$, $Size_{it}$, BM_{it}, $Leverage_{it}$, $MajorExchange_{it}$, DQ_{it}, $FirmAge_{it}$, and $NewFirm_{i}$, and are included as main effects when their inclusion is noted. All continuous control variables (except DQ_{it}, which is bound by 0 and 1, and $PeerBacklog_{it}$) are winsorized at the 1st and 99th percentiles (note: earnings and returns variables are truncated in sample selection). See Appendix D for full variable descriptions. Standard error clustering and the inclusion of fixed effects are as indicated in the table, in which F=firm, Y=year, and I=industry. Industries are defined using 4-digit NAICS codes. T-statistics based are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table 4: Investment efficiency

Panel A: Test of hypothesis 2

	Full sample		Matched sample	
	(1)	(2)	(3)	(4)
VARIABLES	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$
$TobinsQ_{it}$	0.007***	0.005***	0.006***	0.003**
	(4.47)	(3.39)	(4.21)	(2.10)
$TobinsQ_{it} \times Discloser_{it}$	**0.004****	**0.003****	**0.004****	**0.003***
	(2.39)	**(2.04)**	**(2.15)**	**(1.74)**
$Discloser_{it}$	-0.011***	-0.011***	-0.011***	-0.009***
	(-3.47)	(-3.49)	(-3.06)	(-2.60)
Control variables				
$Size_{it}$	0.005***	0.006***	0.006***	0.007***
	(8.12)	(9.42)	(7.70)	(9.49)
$SalesVolatility_{it}$	-0.070***	-0.069***	-0.041	-0.041
	(-3.00)	(-3.07)	(-1.39)	(-1.25)
PPE_{it}	0.075***	0.070***	0.075***	0.073***
	(11.32)	(12.58)	(10.74)	(11.79)
$Leverage_{it}$	0.010*	-0.013**	0.007	-0.015**
	(1.91)	(-1.96)	(1.15)	(-2.20)
$CFOSale_{it}$	0.004	0.020	-0.019	-0.000
	(0.22)	(1.25)	(-0.90)	(-0.02)
$Cash_{it}$	0.031***	0.024***	0.039***	0.032***
	(4.69)	(4.25)	(5.33)	(4.52)
$Dividend_{it}$	-0.010***	-0.009***	-0.010***	-0.008***
	(-4.21)	(-4.22)	(-4.12)	(-3.90)
$FirmAge_{it}$	-0.015***	-0.009***	-0.016***	-0.010***
	(-6.85)	(-5.08)	(-6.96)	(-4.70)
$RNOA_{it}$	-0.022***	-0.027***	-0.016***	-0.023***
	(-4.59)	(-6.23)	(-3.10)	(-4.74)
$Loss_{it}$	-0.007***	-0.006***	-0.006***	-0.007***
	(-3.62)	(-3.56)	(-3.15)	(-3.37)
Ret_{it}	0.006***	0.007***	0.007***	0.009***
	(3.44)	(7.03)	(4.17)	(4.84)
Intercept	0.023***	0.076***	0.022**	0.066***
	(2.98)	(4.88)	(2.53)	(3.84)
Matching controls	No	Yes	No	Yes
Fixed effects	No	I, Y	No	I, Y
Standard error clustering	F, Y	F	F, Y	F
Observations	11,680	11,680	13,742	13,742
R^2	0.225	0.310	0.229	0.315

Table 4, continued.
Panel B: Cross-sectional test

	Full sample				Matched sample			
	MTS_{it} = 0		MTS_{it} = 1		MTS_{it} = 0		MTS_{it} = 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$	$Capex_{it+1}$
$TobinsQ_{it}$	0.007***	0.005***	0.006**	0.004*	0.005***	0.003*	0.009**	0.007**
	(4.33)	(3.45)	(2.51)	(1.73)	(3.10)	(1.66)	(2.34)	(2.01)
$TobinsQ_{it}$ × $Discloser_{it}$	0.005**	0.003*	0.002	0.002	0.005**	0.004**	-0.001	-0.002
	(2.47)	(1.91)	(0.78)	(0.69)	(2.53)	(2.13)	(-0.33)	(-0.48)
$Discloser_{it}$	-0.014***	-0.012***	-0.007*	-0.007	-0.012***	-0.011***	-0.003	-0.002
	(-3.78)	(-3.25)	(-1.78)	(-1.53)	(-3.01)	(-2.75)	(-0.54)	(-0.30)
Investment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matching controls	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	No	I, Y	No	I, Y	No	I, Y	No	I, Y
Standard error clustering	F, Y	F	F, Y	F	F, Y	F	F, Y	F
Observations	8,603	8,603	3,077	3,077	10,759	10,759	2,983	2,983
R^2	0.238	0.329	0.184	0.242	0.237	0.329	0.205	0.286

This table presents the results of estimating equation 2 and variations of this model. $Capex_{it+1}$ equals capital expenditures in fiscal year t + 1 scaled by sales in fiscal year t. $TobinsQ_{it}$ measures the firm's Tobin's Q ratio, which is the market value of assets relative to the book value of assets and is a measure of investment opportunities. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year t and zero otherwise. Panel B presents the results of cross-sectional tests of investment efficiency for firms that follow different business models (MTS_{it}). Specifically, firms are classified as following a make-to-stock business model (MTS_{it} = 1) if the proportion of total inventory held as finished goods is greater than 0.50. $Size_{it}$ measures the natural log of market value of equity at the end of the fiscal year. $SalesVolatility_{it}$ is the quarterly sales volatility over the prior two years. PPE_{it} is property, plant, and equipment scaled by total assets. $Leverage_{it}$ equals the firm's market leverage ratio. $CFOSale_{it}$ equals the ratio of operating cash flows to sales. $Cash_{it}$ equals the ratio of cash holdings to total assets. $Dividend_{it}$ is an indicator variable equal to one if the firm paid a dividend. $FirmAge_{it}$ is the natural log of one plus the number of years since the firm's first fiscal year of available accounting data. $RNOA_{it}$ is calculated as operating income after depreciation divided by average net operating assets. $Loss_{it}$ is an indicator variable equal to one if the firm reports a loss in earnings before extraordinary items. Ret_{it} measures the twelve-month buy-and-hold return beginning three months after the end of fiscal year t – 1. Investment controls include $Size_{it}$, $SalesVolatility_{it}$, PPE_{it}, $Leverage_{it}$, $CFOSale_{it}$, $Cash_{it}$, $Dividend_{it}$, $FirmAge_{it}$, $RNOA_{it}$, $Loss_{it}$, and Ret_{it}. Matching controls include $FinishedGoods_{it}$, $GrossMargin_{it}$, $|Accruals_{it}|$, $GovCustomer_{it}$, $MajorCustomer_{it}$, $Advertising_{it}$, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, $DeclineFirm_{it}$, $PeerBacklog_{it}$, $MajorExchange_{it}$, DQ_{it}, and $NewFirm_{i}$. All continuous variables (except Ret_{it} *and* $RNOA_{it}$, which are truncated in the sample selection) are winsorized at the 1st and 99th percentiles. See Appendix D for full variable descriptions. Standard error clustering and the inclusion of fixed effects are as indicated in the table, in which F=firm, Y=year, and I=industry. Industries are defined using 4-digit NAICS codes. T-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table 5: Persistence of operating profitability

Panel A: Test of hypothesis 3

	Full sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$
$RNOA_{it}$	0.688***	0.613***	0.610***	0.704***	0.626***	0.626***
	(29.92)	(22.81)	(30.81)	(27.52)	(23.33)	(19.87)
$RNOA_{it}$ × $Discloser_{it}$	**-0.022**	**-0.037**	**-0.032**	**-0.039**	**-0.043***	**-0.040**
	(-0.86)	**(-1.49)**	**(-1.38)**	**(-1.27)**	**(-1.93)**	**(-1.27)**
$Discloser_{it}$	0.019***	0.016**	0.015***	0.013	0.011	0.011
	(2.70)	(2.46)	(2.80)	(1.04)	(1.09)	(1.52)
Intercept	0.008	-0.184***	-0.139***	0.014	-0.187***	-0.148***
	(0.92)	(-3.79)	(-4.21)	(1.05)	(-3.04)	(-3.08)
Matching controls	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	I, Y	No	No	I, Y
Standard error clustering	F, Y	F, Y	F	F, Y	F, Y	F
Observations	11,680	11,680	11,680	13,742	13,742	13,742
R^2	0.458	0.495	0.514	0.461	0.499	0.520

Table 5, continued.
Panel B: Cross-sectional test

	Full sample				Matched sample			
	MTS_{it} = 0		MTS_{it} = 1		MTS_{it} = 0		MTS_{it} = 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$
$RNOA_{it}$	0.697***	0.623***	0.661***	0.565***	0.712***	0.641***	0.649***	0.542***
	(26.00)	(29.64)	(20.65)	(14.08)	(23.59)	(18.66)	(9.49)	(8.63)
$RNOA_{it}$ × $Discloser_{it}$	**-0.039**	**-0.048***	**0.034**	**0.011**	**-0.056***	**-0.057***	**0.046**	**0.039**
	(-1.61)	**(-1.95)**	**(0.57)**	**(0.20)**	**(-1.76)**	**(-1.72)**	**(0.57)**	**(0.57)**
$Discloser_{it}$	0.026***	0.017***	0.008	0.010	0.020	0.013	-0.013	-0.004
	(3.10)	(2.66)	(0.74)	(0.86)	(1.54)	(1.61)	(-0.91)	(-0.29)
Intercept	-0.001	-0.137***	0.025***	-0.210***	0.005	-0.173***	0.047***	-0.174*
	(-0.08)	(-3.19)	(3.47)	(-3.21)	(0.34)	(-3.03)	(3.26)	(-1.93)
Matching controls	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	No	I, Y	No	I, Y	No	I, Y	No	I, Y
Standard error clustering	F, Y	F	F, Y	F	F, Y	F	F, Y	F
Observations	8,603	8,603	3,077	3,077	10,759	10,759	2,983	2,983
R^2	0.457	0.518	0.459	0.516	0.460	0.523	0.461	0.521

This table presents results of estimating equation 3 and variations of this model. $RNOA_{it}$ is calculated as operating income after depreciation divided by average net operating assets. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year *t* and zero otherwise. Firms are classified as following a make-to-stock business model (MTS_{it} = 1) if the proportion of total inventory held as finished goods ($FinishedGoods_{it}$) is greater than 0.50. Matching controls include $FinishedGoods_{it}$, $GrossMargin_{it}$, $|Accruals_{it}|$, $GovCustomer_{it}$, $MajorCustomer_{it}$, $Advertising_{it}$, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, $DeclineFirm_{it}$, $PeerBacklog_{it}$, $Size_{it}$, BM_{it}, $Leverage_{it}$, $MajorExchange_{it}$, DQ_{it}, $FirmAge_{it}$, and $NewFirm_{i}$. All continuous control variables (except DQ_{it}, which is bound by 0 and 1, and $PeerBacklog_{it}$) are winsorized at the 1st and 99th percentiles. $RNOA_{it+1}$ and $RNOA_{it}$ are truncated at -/+ 1 in sample selection. See Appendix D for full variable descriptions. Standard error clustering and the inclusion of fixed effects are as indicated in the table, in which F=firm, Y=year, and I=industry. Industries are defined using 4-digit NAICS codes. T-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table 6: Management forecasts and forward earnings response coefficients

	Full sample		Matched sample	
	(1)	(2)	(3)	(4)
VARIABLES	Ret_{it}	Ret_{it}	Ret_{it}	Ret_{it}
$Earn_{it-1}$	-1.201***	-1.210***	-1.059***	-1.056***
	(-3.68)	(-3.71)	(-2.74)	(-2.74)
$Earn_{it}$	0.371*	0.342*	0.529***	0.520***
	(1.81)	(1.65)	(2.65)	(2.60)
$Earn_{it+1}$	1.835***	1.819***	1.563***	1.558***
	(8.12)	(7.99)	(4.48)	(4.51)
Ret_{it+1}	-0.216***	-0.213***	-0.192**	-0.191**
	(-3.34)	(-3.31)	(-2.33)	(-2.29)
$Earn_{it-1} \times Discloser_{it}$	0.203	0.169	0.055	0.015
	(1.03)	(0.90)	(0.35)	(0.11)
$Earn_{it} \times Discloser_{it}$	-0.320	-0.352	-0.498**	-0.544***
	(-1.41)	(-1.50)	(-2.34)	(-2.71)
$Earn_{it+1} \times Discloser_{it}$	0.707***	0.665***	1.012***	0.957**
	(3.23)	(3.13)	(2.69)	(2.56)
$Ret_{it+1} \times Discloser_{it}$	0.047	0.050	0.024	0.027
	(1.31)	(1.36)	(0.50)	(0.57)
$Discloser_{it}$	-0.041***	-0.044***	-0.028	-0.032*
	(-3.00)	(-2.85)	(-1.45)	(-1.77)
$Forecast_t$	0.179		0.054	0.179
	(1.28)		(0.36)	(1.28)
$Forecast_t \times Discloser_{it}$	0.194		0.290**	0.194
	(1.03)		(2.36)	(1.03)
Intercept	0.121**	0.118**	0.108**	0.107**
	(2.11)	(2.04)	(2.01)	(1.99)
F-test [($Earn_{it+1} \times Discloser_{it}$) + ($Ret_{it+1} \times Discloser_{it}$ = 0)]	**12.50*** **	**11.76*** **	**8.41*** **	**7.69*** **
F-stat [$Forecast_t$ + ($Forecast_t \times Discloser_{it}$) = 0]		**8.85*** **		**6.11** **
FERC controls	No	No	No	No
Matching controls	No	No	No	No
Observations	3,733	3,733	4,115	4,115
R^2	0.206	0.209	0.205	0.206

This table presents results of estimating equation 4. Ret_{in} measures the twelve-month buy-and-hold return beginning three months after the end of fiscal year n – 1. $Earn_{in}$ is calculated as earnings before extraordinary items in fiscal year n divided by market value of equity three months after the end of fiscal year t – 1. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year t and zero otherwise. $Forecast_{it}$ is the dollar value of managers EPS forecast, scaled by the firm's stock price three months after the end of fiscal year t – 1. If management provides a range forecast, I use the lower bound as the dollar value of the forecast. I drop observations where the absolute value of $Forecast_{it}$ is greater than one (note: earnings and returns variables are truncated in sample selection). FERC controls include $Loss_{it}$, $Beta_{it}$, $Coverage_{it}$, $Size_{it}$, BM_{it}, and an indicator variable equal to one if Ret_{it} is less than zero. Matching controls include $FinishedGoods_{it}$, $GrossMargin_{it}$, $|Accruals_{it}|$, $GovCustomer_{it}$, $MajorCustomer_{it}$, $Advertising_{it}$, $GrowthFirm_{it}$, $MatureFirm_{it}$, $ShakeoutFirm_{it}$, $DeclineFirm_{it}$, $PeerBacklog_{it}$, $Size_{it}$, BM_{it}, $Leverage_{it}$, $MajorExchange_{it}$, DQ_{it}, $FirmAge_{it}$, and $NewFirm_i$. See Appendix D for full variable descriptions. T-statistics based on standard errors clustered by firm and year are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Appendix A: Regulation excerpt and example disclosures

A.1. Regulatory requirement to disclose order backlog

Regulation S-K (17 C.F.R. § 229.101) (Item 101) Description of Business

(c) (viii) The dollar amount of backlog orders believed to be firm, as of a recent date and as of a comparable date in the preceding fiscal year, together with an indication of the portion thereof not reasonably expected to be filled within the current fiscal year, and seasonal or other material aspects of the backlog. (There may be included as firm orders government orders that are firm but not yet funded and contracts awarded but not yet signed, provided an appropriate statement is added to explain the nature of such orders and the amount thereof. The portion of orders already included in sales or operating revenues on the basis of percentage of completion or program accounting shall be excluded.)

A.2. Example of disclosure of low materiality order backlog

Excerpt from the 2014 10-K of Plantronics

Our backlog of unfilled orders was $24.3 million and $26.6 million at March 31, 2015 and 2014, respectively. We include all purchase orders scheduled for future delivery in backlog. We have a "book and ship" business model whereby we fulfill the majority of orders within 48 hours of receipt of the order. As a result, our net revenues in any fiscal year depend primarily on orders booked and shipped in that year. In addition, our backlog is occasionally subject to cancellation or rescheduling by the customer on short notice with little or no penalty. Therefore, there is a lack of meaningful correlation between backlog at the end of a fiscal year and the following fiscal year's net revenues. Similarly, there is a lack of meaningful correlation between year-over-year changes in backlog as compared with year-over-year changes in net revenues. As a result, we do not believe that backlog information is material to an understanding of our overall business.

A.3. Example of non-disclosure with existence of order backlog

Excerpt from the 2014 10-K of Integrated Silicon Solution

Our sales are generally made pursuant to standard purchase orders, which can be revised by our customers to reflect changes in the customer's requirements. Generally, our purchase orders and OEM agreements allow customers to reschedule delivery dates and cancel purchase orders without significant penalties. For these reasons, we believe that our backlog, while useful for scheduling production, is not necessarily a reliable indicator of future revenues. To meet customer requirements, we often must deliver products on relatively short notice. Accordingly, we must maintain a significant inventory of certain items to be able to meet these requirements.

Appendix B: Propensity score matching

To identify the effects of disclosing order backlog, ideally I could observe random variation in whether a firm discloses order backlog. In the absence of exogenous variation, however, any differences in firm outcomes for disclosers and non-disclosers are subject to concerns that an omitted variable is correlated with a firm's backlog disclosure policy as well as the outcome variable of interest (e.g., investment efficiency).

One obvious potential difference between disclosers and non-disclosers is the existence of backlog. That is, one reason some firms do not disclose backlog is because they do not have this information to report. Although I select a sample of firms from industries in which I expect this is less problematic, there could be error in this assumption. Even amongst firms that have material order backlog, however, there could also be other characteristics that differ between disclosers and non-disclosers. For instance, because backlog disclosures were more common in the 1970s and 1980s than in my sample period (Figure 1), older firms may be more likely to have a history of reporting backlog. Older firms could also make more efficient investments, not because they disclose backlog, but because they have better systems and policies in place to evaluate investment opportunities. Therefore, any relation between disclosing backlog and investment efficiency could be attributable to differences in the age of disclosers and non-disclosers.

I construct a matched sample using propensity score matching to mitigate concerns that observable differences between disclosers and non-disclosers explain my results. To estimate the propensity scores I use a logit regression in which the dependent variable equals one if the firm discloses backlog in year t and zero otherwise ($Discloser_{it}$). The purpose of the matching procedure is twofold: 1) to investigate whether and how disclosers and non-disclosers differ among several characteristics that I expect are correlated with the materiality of order backlog, and 2) to create a matched sample of firms based on these and other characteristics that could be correlated both with whether a firm discloses backlog and the proxies used in testing my hypotheses. For these reasons, I select independent variables for the model that represent firm characteristics that could be correlated with the existence of material order backlog as well as other innate firm characteristics that could represent omitted variables in the tests of my hypotheses.[1] I discuss the rationale for and measurement of these variables below. Because firms typically commit to a specific disclosure practice, I examine relatively persistent firm characteristics.

I winsorize all continuous variables at the 1st and 99th percentiles and present the coefficient estimates after clustering standard errors by firm. I also include year and industry fixed effects as Figure 1 illustrates a downward trend in the probability of disclosing backlog over time and the average proportion of disclosers varies across industries (see Appendix C).[2] The results of the propensity score model are presented in Table 1.

Business model

Firms can follow different business models both within an industry and over time. For instance, in manufacturing industries, firms can follow a make-to-order or make-to-stock business model (or some combination thereof). In the former case, at the extreme, the firm does not begin production until a purchase order is received from a customer. Therefore, at any given date, these firms are more likely to have material order backlog. In contrast, if a firm makes-to-stock, managers forecast demand and produce goods to subsequently deliver to customers within a short time period after receiving a purchase order. I proxy for the extent to which a firm follows a make-to-stock business model by calculating the proportion of total inventory held as finished goods ($FinishedGoods_{it}$). I expect that firms that follow more of a make-to-stock business model will have a greater proportion of total inventory held as finished goods on average. I find a negative coefficient on $FinishedGoods_{it}$, suggesting that disclosers follow more of a make-to-order business model on average.

Product type

I next examine whether disclosers have different types of products on average (e.g., product uniqueness). On the one hand, it is possible that firms with more unique products would be more likely to receive orders in advance, particularly if these had to be manufactured with particular specifications. On the other hand, anecdotal evidence suggests that some firms may be subject to double-ordering from customers, which may result in greater order quantities and thus, a greater likelihood of having material order backlog. Therefore, it is unclear ex ante whether and how

[1] There is a tradeoff in controlling for some characteristics to the extent they are correlated with the discretion managers exercise over the disclosure policy. In particular, including some of these variables could partially control for some of the effects I am testing.

[2] Inferences are similar without fixed effects and if the model is estimated using a probit regression.

product type would differ for disclosers and non-disclosers. To examine differences in product type for disclosers and non-disclosers, I include measures of a firm's R&D intensity (*LnR&D*$_{it}$) and gross margin (*GrossMargin*$_{it}$). R&D intensity is measured as the log of 1+R&D/Sales. I set missing values of R&D to zero and winsorize R&D/Sales at 1. I find that disclosers have significantly lower R&D intensity and gross margins. To the extent that these variables capture the degree of product uniqueness, this suggests that firms with more unique products are less likely to have material order backlog.[3]

Sales volatility and accruals

If firms with order backlog generate revenue by receiving orders in advance, managers may be more able to compensate for changes in demand (e.g., advance notice of a customer loss could allow managers to seek new customers in a more timely manner and avoid a negative shock to sales). If this is the case, disclosers could have lower sales volatility than non-disclosers. I measure sales volatility as the standard deviation of quarterly sales (scaled by average assets) over the prior two years (*SalesVolatility*$_{it}$). Although I find that disclosers have significantly lower sales volatility on a univariate basis (see Table 2, Panel C), the significance of this association does not extend to the multivariate setting (two-tailed p-value = 0.141).[4]

I also examine whether disclosers require less estimation in their accounting system and include the magnitude of accruals ($|Accruals_{it}|$). I find a negative association between the absolute value of operating accruals and a firm's backlog disclosure policy, suggesting that disclosers could be required to make fewer estimates in reporting firm performance.

Customer base

A firm's customer base could also affect whether it has material order backlog and thus represent an important difference between disclosers and non-disclosers. For instance, because government agencies secure funding through state or federal budgeting processes, they are more likely to place orders in advance. Using Compustat's segment database to identify firms that

[3] The literature on proprietary costs of disclosure often uses R&D and gross margin as proxies for proprietary costs (e.g., Li 2010; Ellis et al. 2012). To the extent managerial discretion has a significant effect on a firm's backlog disclosure policy, this negative association could reflect a reluctance to disclose backlog when proprietary cost concerns are high.

[4] Additionally, if managers of firms with order backlog are able to manage recognized revenue by speeding up or delaying order fulfillment (Gilliam 2013), they could utilize this discretion to ensure a smooth revenue stream. Therefore, firms with material backlog could have smoother revenue streams because of their ability to manage revenue (relative to firms without order backlog). This would not provide an explanation for any difference between disclosers and non-disclosers conditional on the existence of backlog.

report a government agency as a major customer, I find that disclosers are more likely to report a government agency as a major customer (*GovCustomer*$_{it}$)

Whether this association extends to corporate customers is less clear ex ante. On the one hand, major corporate customers may be less likely to place orders in advance because the firms could have well integrated supply chains (Patatoukas 2012).[5] On the other hand, the existence of a major customer could indicate the importance of a firm's product for the customer, which could lead to advance ordering. To examine these potential differences, I include an indicator variable equal to one for the existence of a major corporate customer (*MajorCustomer*$_{it}$).[6] I find that disclosers are less likely to report a major corporate customer on average, although this association is not significant at conventional two-tailed levels (p-value = 0.140).

Finally, although many manufacturers sell their products to other businesses or through distributors, some also sell directly to consumers. Firms that sell directly to consumers could receive fewer orders in advance, reducing the likelihood that the firm would have material order backlog. I proxy for the extent to which the firm sells directly to consumers by including an indicator variable equal to one if the firm discloses non-zero advertising expense in year *t* and zero otherwise (*Advertising*$_{it}$). I find that disclosers are significantly less likely to report advertising expense.

Capacity and demand

The existence of material order backlog is also likely to be a function of whether a firm has a pipeline in place to sell its products (i.e., the extent of demand) and whether it is able to meet this demand in the short-term (i.e., does it have the productive capacity). I examine whether disclosers are at a different life cycle stage than non-disclosers using the life cycle classification approach in Dickinson (2011), which is based on the pattern of cash flows from operating, investing, and financing activities. It is unclear how a firm's life cycle would be associated with the existence of material order backlog. For example, mature firms are more likely to have an established customer base but also more likely to have the capacity to meet demand. I use

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[5] The existence of a major corporate customer could increase any proprietary costs associated with disclosing order backlog by providing additional information to competitors that might be helpful if trying to acquire these orders (Ellis et al. 2012).

[6] Firms are required to disclose whether any customer constitutes at least 10% of their annual revenue. However, there are firms that disclose less material customer relationships in terms of dollar amounts, but do constitute a significant customer relationship. Following prior literature, I consider only major customer relationships that amount to at least 10% of revenue (Patatoukas 2012; Dhaliwal et al. 2015).

introduction firms as the base category and include indicator variables for the other four life cycle groups. Accordingly, the coefficients on each life cycle group are interpreted as the probability of disclosing backlog relative to introduction firm-years. I find that growth, mature, and shakeout firms are significantly more likely to disclose backlog than introduction firms but no significant differences between firms in the introduction and decline life cycle stages.

Materiality of backlog

The materiality of backlog likely differs across industries. Although I include industry fixed effects in estimating the propensity score model on a pooled sample, there is also within industry variation in disclosure trends, which could represent changes in the materiality of order backlog at the industry-level. Therefore, I calculate the materiality of backlog (measured as order backlog relative to sales; $Backlog_{it}$) for peer firms in the industry that disclose backlog in year t and include this variable in the model ($PeerBacklog_{it}$).[7] I find that the probability of disclosing order backlog is increasing in the materiality of peer firm's backlog.

Other firm characteristics

I also control for firm size, measured as the natural log of market value of equity at the end of year t ($Size_{it}$), growth opportunities, measured as the book-to-market ratio at the end of year t (BM_{it}), market leverage ($Leverage_{it}$), and whether or not the firm is listed on a major stock exchange—specifically, the NYSE, NASDAQ, or AMEX ($MajorExchange_{it}$). I find no significant differences between disclosers and non-disclosers across these characteristics.

As a control for general disclosure quality, I calculate the value-weighted proportion of non-missing balance sheet items (DQ_{it}) using the methodology outlined in Chen et al. (2015). The results in Table 1 reveal that disclosers report more disaggregated data in their balance sheet on average.

I find that disclosers are significantly older firms on average ($FirmAge_{it}$). I also include an indicator variable equal to one for firms that went public during my sample period ($NewFirm_i$) and find a negative coefficient in Table 1. This supports the idea that the declining trend in the

[7] An alternative would be to estimate the model by industry. I choose to include industry-year level controls rather than estimate within industry because estimating within an industry restricts the number of observations available to match with. Thus, by estimating on a pooled sample, I increase the possibility of finding appropriate matches. Moreover, because I focus on a single sector (manufacturing) and industry classifications are imperfect, there may be some overlap in industry classifications for some firms.

proportion of firms disclosing backlog is largely attributable to new firms not disclosing this information rather than firms ceasing to provide this disclosure (see also Figure 2).

Summary

Although I find numerous differences between firms reporting and not reporting backlog in Table 1, the independent variables explain significant variation in discloser status; the model has a pseudo R-squared of 0.145 and an area under the ROC curve of 0.752.[8] Overall, these diagnostic statistics demonstrate the predictive strength of the model and illustrate that observable firm and industry characteristics explain a significant amount of variation in firms' backlog disclosure policies. Despite significant differences in their average characteristics, there is overlap in the propensity scores from the model for disclosers and non-disclosers (i.e., there is substantial common support). As a result, I identify non-disclosers with similar innate characteristics to disclosers and create a matched sample. To do so, I implement nearest neighbor matching within a 0.05 caliper. I match with replacement because I have fewer non-disclosers than disclosers in my full sample. Because of the common support that is evident in Panel A of Figure 3, matching with replacement allows me to retain all but 68 discloser firm-years. Thus, the matched sample consists of 13,742 firm-year observations.

As support for the economic characteristics I use in the propensity score model, I examine how the propensity scores are correlated with the materiality of backlog, as reported by disclosers. Because a number of the propensity score covariates are chosen with the expectation of being correlated with the existence of material order backlog, I expect that the propensity score should be positively correlated with the materiality of backlog (backlog intensity). I sort observations into quartiles based on the propensity score and present the number of disclosers and non-disclosers in each quartile, the propensity score cutoffs used to assign observations into quartiles, and descriptive statistics of the backlog intensity for disclosers ($Backlog_{it}$). I present this information in Table B.1. I find that backlog intensity is monotonically increasing across quartiles for both samples.

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[8] The ROC (receiver operating characteristics) curve plots the fraction of disclosers correctly classified against the fraction of non-disclosers incorrectly classified as the classification cutoff varies. The greater the area under the curve, the better the predictive power of the model, with an area of 1.0 representing a perfectly predictive model (Cameron and Travedi 2005).

Table B.1: Propensity score quartiles and backlog materiality

Panel A: Full sample

	Number of observations		$Propensity_{it}$		$Backlog_{it}$			
Quartile	$Discloser_{it} = 0$	$Discloser_{it} = 1$	Min	Max	Mean	25th Percentile	Median	75th Percentile
1	1,947	973	0.016	0.440	0.210	0.063	0.148	0.269
2	1,481	1,439	0.440	0.604	0.231	0.092	0.175	0.298
3	938	1,982	0.605	0.756	0.298	0.118	0.215	0.368
4	375	2,545	0.756	0.998	0.551	0.210	0.378	0.726

Panel B: Matched sample

	Number of observations		$Propensity_{it}$		$Backlog_{it}$			
Quartile	$Discloser_{it} = 0$	$Discloser_{it} = 1$	Min	Max	Mean	25th Percentile	Median	75th Percentile
1	1,719	1,718	0.052	0.538	0.220	0.072	0.163	0.279
2	1,714	1,720	0.538	0.687	0.251	0.102	0.186	0.326
3	1,721	1,715	0.687	0.808	0.371	0.144	0.266	0.459
4	1,717	1,718	0.809	0.987	0.583	0.228	0.412	0.768

Panel A (B) presents summary information on the composition of firms across quartiles of the propensity scores estimated in Table 1 ($Propensity_{it}$) for the full (matched) sample. In particular, the cutoffs of the propensity scores used to split observations into a quartile, as well as the number of disclosers and non-disclosers in each quartile are presented. I also provide the distribution of the materiality of order backlog ($Backlog_{it}$) amongst the disclosers in each quartile. $Discloser_{it}$ is an indicator variable equal to one if the firm discloses order backlog in fiscal year *t* and zero otherwise.

Appendix C: Sample description

Table C.1: Sample selection

	Number of firm-years	**Number of industries**
Firm-years from manufacturing industries in which the average proportion of U.S. firms disclosing backlog in an industry-year averages at least 25% from 1996-2014	24,555	21
Less: Firm-years with incomplete data to estimate the propensity score model and hypothesis tests	16,144	21
Less: Firm-years with absolute value of price at the beginning of the return cumulation period less than $1	15,667	21
Less: Firm-years with returns in year *t* or *t* + 1 in the top and bottom 1% of the distribution or $\lvert Earn_{t-1}\rvert$, $\lvert Earn_{t}\rvert$, $\lvert Earn_{t+1}\rvert$, $\lvert RNOA_{t}\rvert$ or $\lvert RNOA_{t+1}\rvert > 1$	13,115	21
Less: Industries with fewer than 300 firm-years (full sample)	11,680	15
Matched sample	13,742	15

Table C.2: Industry composition and descriptive statistics by industry

Panel A: Full sample

Industry name	4-digit NAICS	N	Mean *Discloser*	Mean *Backlog*	Std. Dev. of *Backlog*	Mean *HHI*
Aerospace Product and Parts Manufacturing	3364	362	0.953	1.077	0.621	0.162
Industrial Machinery Manufacturing	3332	548	0.887	0.311	0.198	0.112
Agriculture, Construction, and Mining Machinery Manufacturing	3331	459	0.743	0.370	0.321	0.119
Electrical Equipment Manufacturing	3353	338	0.707	0.345	0.376	0.283
Other General Purpose Machinery Manufacturing	3339	587	0.690	0.317	0.277	0.089
Communications Equipment Manufacturing	3342	1,205	0.671	0.369	0.383	0.117
Other Fabricated Metal Product Manufacturing	3329	360	0.644	0.536	0.425	0.128
Commercial and Service Industry Machinery Manufacturing	3333	418	0.620	0.259	0.304	0.219
Other Electrical Equipment and Component Manufacturing	3359	444	0.581	0.366	0.438	0.081
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	3345	2,186	0.572	0.377	0.432	0.077
Semiconductor and Other Electronic Component Manufacturing	3344	2,114	0.571	0.320	0.283	0.046
Cut and Sew Apparel Manufacturing	3152	434	0.468	0.311	0.141	0.110
Plastics Product Manufacturing	3261	449	0.443	0.133	0.110	0.073
Computer and Peripheral Equipment Manufacturing	3341	1,154	0.409	0.217	0.293	0.110
Other Miscellaneous Manufacturing	3399	622	0.378	0.154	0.136	0.104

Panel B: Matched sample

Industry name	4-digit NAICS	N	Mean *Discloser*	Mean *Backlog*	Std. Dev. of *Backlog*	Mean *HHI*
Aerospace Product and Parts Manufacturing	3364	468	0.592	1.042	0.611	0.167
Industrial Machinery Manufacturing	3332	862	0.564	0.311	0.198	0.109
Agriculture, Construction, and Mining Machinery Manufacturing	3331	727	0.469	0.370	0.321	0.118
Electrical Equipment Manufacturing	3353	542	0.441	0.345	0.376	0.278
Other General Purpose Machinery Manufacturing	3339	932	0.435	0.317	0.277	0.088
Communications Equipment Manufacturing	3342	1,718	0.470	0.369	0.383	0.111
Other Fabricated Metal Product Manufacturing	3329	431	0.538	0.536	0.425	0.127
Commercial and Service Industry Machinery Manufacturing	3333	522	0.496	0.259	0.304	0.216
Other Electrical Equipment and Component Manufacturing	3359	453	0.570	0.366	0.438	0.080
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	3345	2,378	0.526	0.377	0.432	0.076
Semiconductor and Other Electronic Component Manufacturing	3344	2,426	0.498	0.320	0.283	0.046
Cut and Sew Apparel Manufacturing	3152	482	0.421	0.311	0.141	0.105
Plastics Product Manufacturing	3261	420	0.474	0.133	0.110	0.070
Computer and Peripheral Equipment Manufacturing	3341	927	0.509	0.217	0.293	0.108
Other Miscellaneous Manufacturing	3399	454	0.518	0.154	0.136	0.099

This table presents summary industry information for firms in the full sample in Panel A and the matched sample in Panel B. *Discloser* is an indicator variable equal to one if the firm discloses order backlog in fiscal year *t* and zero otherwise. *Backlog* is a measure of the materiality of order backlog, calculated as the dollar amount of reported backlog from Compustat, divided by contemporaneous sales. *HHI* is the sales concentration ratio.

Appendix D: Variable list

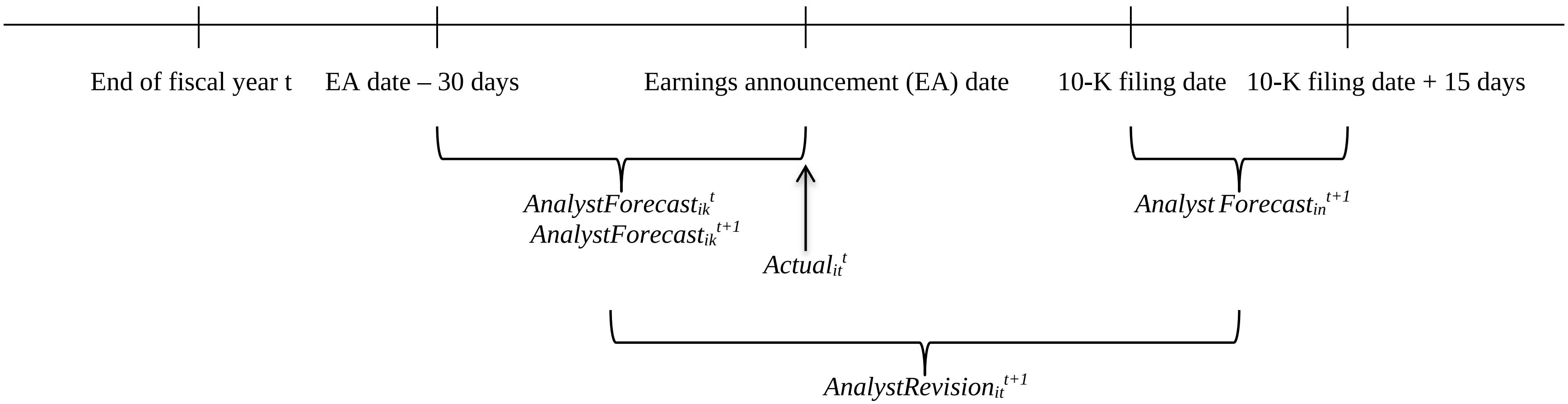
Variable	Description
$\lvert Accruals_{it}\rvert$	Absolute value of operating accruals (Compustat items IBC-OANCF) scaled by average total assets in year *t*
$Advertising_{it}$	Indicator variable equal to one if the firm reports non-zero advertising expense and zero otherwise (Compustat item XAD)
$\Delta AnalystFollow_{it}$	Percentage change in the number of analysts in the consensus forecast for fiscal year *t* + 1 from the most recent consensus prior to the earnings announcement to the first consensus forecast provided within 15 days after the fiscal year *t* 10-K filing date
$\sigma(AnalystForecast_{it})$	Standard deviation of most recent median consensus forecast for fiscal year *t* + 1 prior to the earnings announcement
$AnalystForecastAge_{it}$	Length of time between the date most recent median consensus forecast for fiscal year *t* + 1 prior to the earnings announcement and the earnings announcement date
$AnalystRevision_{it}^{t+1}$	Measures the change in the most recent median consensus forecast (EPS or sales) for fiscal year *t* + 1 from prior to the earnings announcement for fiscal year *t* to the first forecast provided within 15 days after the fiscal year *t* 10-K filing date, divided by the firm's stock price or market value of equity at the end of fiscal year *t* (for EPS and sales forecasts respectively)
$Beta_{it}$	Market beta calculated over the prior five years with a minimum of 12 months of observations, measured three months after the end of fiscal year *t*
$Backlog_{it}$	Order backlog divided by sales for fiscal year *t* (Compustat items OB/SALE)
$\%\Delta Backlog_{it}$	Percentage change in $Backlog_{it}$
BM_{it}	Book-to-market ratio at the end of fiscal year *t* (Compustat items CEQ/(PRCC_F×CSHO))
$Capex_{it+1}$	Capital expenditures in fiscal year *t* +1 scaled by sales in fiscal year *t* (Compustat items CAPX/SALE)
$Cash_{it}$	Cash holdings scaled by total assets at the end of fiscal year *t* (Compustat items CHE/AT)
$OpCashFlows_{it}$	Cash flows from operations (Compustat item OANCF), scaled by average total assets in fiscal year *t* (Compustat item AT)
$CFOSale_{it}$	Ratio of operating cash flows to sales in fiscal year *t* (Compustat items OANCF/SALE)
$Coverage_{it}$	Indicator variable equal to one if analysts provide either an annual or quarterly sales or earnings forecast during the period after the firm's fiscal year end to ten days after the filing date of the 10-K, and zero otherwise
$DeclineFirm_{it}$	Indicator variable equal to one if the cash flows classify the firm-year as a decline firm, as per Dickinson (2011), and zero otherwise
$Discloser_{it}$	Indicator variable equal to one if the firm reports non-zero order backlog in year *t* and zero otherwise (Compustat item OB)
$Dividend_{it}$	Indicator variable equal to one if the firm paid a dividend in fiscal year *t* (Compustat item DV)
DQ_{it}	Disclosure quality measure based on the proportion of non-missing items from the balance sheet, as discussed in Chen et al. (2015)
E_{it}	Earnings before extraordinary items in fiscal year *t* (Compustat item IBC), scaled by average total assets in fiscal year *t* (Compustat item AT)
$Earn_{it}$	Earnings before extraordinary items in fiscal year *t* (Compustat item IB), scaled by market value of equity three months after the end of fiscal year *t* – 1

E_Index_{it}	Count variable that ranges from zero to six in which a firm receives one point for the existence of each of the following governance provisions: staggered board, limits to shareholder amendments of bylaws, supermajority requirements for mergers and charter amendments, poison pills, and golden parachutes. The variable is decreasing in governance quality (Bebchuk et al. 2009)
$FinishedGoods_{it}$	Proportion of total inventory held as finished goods (Compustat items INVFG/INVT). Missing values are set to zero
$FirmAge_{it}$	Natural log of 1 + firm age; firm age is calculated as the difference between the current fiscal year and the first fiscal year for which the firm has accounting data on Compustat
$Forecast_{it}$	Dollar value of the most recent management EPS forecast for fiscal year t + 1 provided in the three months subsequent to the end of fiscal year *t*, scaled by the firm's stock price three months after the end of fiscal year *t* – 1. If management provides a range forecast, I use the lower bound as the dollar value of the forecast
$GrossMargin_{it}$	Gross margin ratio (Compustat items (SALE-COGS)/SALE)
$GovCustomer_{it}$	Indicator variable equal to one if the firm reports a government agency as a major customer and zero otherwise
$GrowthFirm_{it}$	Indicator variable equal to one if the cash flows classify the firm-year as a growth firm, as per Dickinson (2011), and zero otherwise
HHI_{jt}	Herfindahl-Hirschman Index for sales concentration ratio in an industry-year, calculated as $\sum^{Nj} (Sale_{ijt}/\sum^{Nj} Sale_{ijt})^2$ where N_j is the number of firms in industry j
$InstOwn_{it}$	Proportion of common shares outstanding held by institutional owners
$IntroFirm_{it}$	Indicator variable equal to one if the cash flows classify the firm-year as an introduction firm, as per Dickinson (2011), and zero otherwise
$\%\Delta Inventory_{it}$	Percentage change in total inventory relative to sales from fiscal year t – 1 to t (Compustat items INVT/SALE)
$Leverage_{it}$	Leverage at the end of year *t* (Compustat items (DLC+DLTT) / (DLC+DLTT+(CSHO*PRCC_F)))
$LnR\&D_{it}$	Natural log of 1 + R&D/Sales (Compustat items XRD/SALE)
$Loss_{it}$	Indicator variable equal to one if the firm reports a loss in year *t* and zero otherwise (Compustat item IBC)
$MajorCustomer_{it}$	Indicator variable equal to one if the firm reports the existence of a major corporate company and zero otherwise (major customers only include those that contribute at least 10% of the company's annual sales)
$MajorExchange_{it}$	Indicator variable equal to one if the firm is listed on the NYSE, AMEX, or NASDAQ and zero otherwise (Compustat item EXCHG)
$MatureFirm_{it}$	Indicator variable equal to one if the cash flows classify the firm-year as a mature firm, as per Dickinson (2011), and zero otherwise
MTS_{it}	Indicator variable equal to one if $FinishedGoods_{it}$ is greater than 0.50 and zero otherwise
$NewFirm_{i}$	Indicator variable equal to one if the first fiscal year of accounting data available for the firm is after 1996
ΔOB_{it}	Change in order backlog from fiscal year *t* – 1 to *t* (Compustat item OB) divided by average total assets in fiscal year *t* (Compustat item AT)
$PeerBacklog_{it}$	Backlog intensity of peer firms, defined as those in the same 4-digit NAICS industry group (Compustat items OB/SALE)
PPE_{it}	Property, plant, and equipment scaled by total assets (Compustat items PPENT/AT)
$Propensity_{it}$	Predicted value of $Discloser_{it}$ based on the propensity score model in Table 1

Ret_{it}	Twelve-month buy-and-hold returns beginning three months after the end of fiscal year *t* – 1. Returns are calculated after accounting for delisting and characteristics following Shumway (1997)
Ret_{it+1}	Twelve month buy-and-hold returns beginning three months after the end of fiscal year *t*. Returns are calculated after accounting for delisting and characteristics following Shumway (1997)
$RNOA_{it}$	Return on net operating assets for fiscal year *t*, calculated as operating income after depreciation divided by average net operating assets (Compustat items OIADP /((DLC + DLTT + MIB + PSTK + CEQ – CHE - IVAO)/2))
$\%\Delta Sales_{it+1}$	Percentage growth in sales from fiscal year *t* to *t* + 1 (Compustat item SALE)
$SalesVolatility_{it}$	Quarterly sales volatility over the prior two years, calculated as the standard deviation of sales divided by average total assets over the prior 8 quarters (Compustat items SALEQ/Average ATQ))
$ShakeoutFirm_{it}$	Indicator variable equal to one if the cash flows classify the firm-year as a shakeout firm, as per Dickinson (2011), and zero otherwise
$Size_{it}$	Natural log of the market value of equity at the end of fiscal year *t* (Compustat items PRCC_F×CSHO)
$Surprise_{it}$	Difference between actual annual performance (EPS or sales) for fiscal year *t* and the most recent analyst median consensus forecast within the 30 days prior to the earnings announcement date, divided by price or market value of equity at the end of fiscal year *t* (for EPS and sales forecasts respectively)
$TobinsQ_{it}$	Tobin's Q (Compustat items (AT + (PRCC_F × CSHO) - CEQ - TXDB) / AT)

Appendix E: Additional analyses

Figure E.1: Timeline of variable measurement for analyst forecast revision tests



This figure presents an overview of the timing of variable measurement for the analyst forecast revision tests presented in Table E.4. Based on the above timeline, the following variables are calculated as follows: $Surprise_{it}$ = ($Actual_{it}^{t}$ - $AnalystForecast_{ik}^{t}$) divided by price or market value of equity (for EPS and sales forecasts respectively). $AnalystRevision_{it}^{t+1}$ = ($AnalystForecast_{in}^{t+1}$ - $AnalystForecast_{ik}^{t+1}$) divided by price or market value of equity (for EPS and sales forecasts respectively). $AnalystForecastAge_{it}$ is the time between the date of $AnalystForecast_{ik}^{t+1}$ and the earnings announcement date. $\sigma(AnalystForecast_{it})$ is the standard deviation of $AnalystForecast_{ik}^{t+1}$ divided by price or market value of equity (for EPS and sales forecasts respectively). $\Delta AnalystFollow_{it}$ is the percentage change in the number of analysts providing forecasts for $AnalystForecast_{ik}^{t+1}$ to $AnalystForecast_{in}^{t+1}$.

Table E.1: Firm-level determinants model

VARIABLES	(1) $Discloser_i$
$FinishedGoods_i$	-0.162***
	(-3.48)
$LnR\&D_i$	-0.142**
	(-2.05)
$GrossMargin_i$	-0.480***
	(-5.88)
$SalesVolatility_i$	-0.027
	(-0.08)
$\lvert Accruals_i \rvert$	-0.616***
	(-3.51)
$GovCustomer_i$	0.193***
	(4.04)
$MajorCustomer_i$	-0.045*
	(-1.70)
$Advertising_i$	-0.105***
	(-4.11)
$GrowthFirm_i$	0.089*
	(1.80)
$MatureFirm_i$	0.092*
	(1.92)
$ShakeoutFirm_i$	0.110*
	(1.69)
$DeclineFirm_i$	0.006
	(0.09)
$PeerBacklog_i$	0.002
	(0.24)
$Size_i$	0.032
	(0.98)
BM_i	-0.034
	(-0.36)
$Leverage_i$	0.013
	(0.45)
$MajorExchange_i$	0.149
	(0.94)
DQ_i	0.072***
	(3.87)
$FirmAge_i$	-0.185***
	(-6.32)
$NewFirm_i$	-0.162***
	(-3.48)
Observations	1,602
R-Squared	0.233

This table presents the results of estimating an OLS regression for the association between a firm's backlog disclosure policy and various firm outcomes on a firm-level basis (i.e., the unit of observation is the firm-level). The dependent variable (*Discloser*$_i$) equals the proportion of years for which the firm has available Compustat data in which it discloses order backlog. The independent variables are calculated as the firm-specific time-series average of the following variables. *FinishedGoods*$_{it}$ equals the proportion of total inventory held as finished goods. *LnR&D*$_{it}$ equals the natural log of one plus R&D expenditures divided by sales. *GrossMargin*$_{it}$ represents the firm's gross margin ratio. *SalesVolatility*$_{it}$ is the quarterly sales volatility over the prior two years. |*Accruals*$_{it}$| measures the absolute value of accruals scaled by total assets. *GovCustomer*$_{it}$ is an indicator variable equal to one if the firm reports a government agency as a major customer. *MajorCustomer*$_{it}$ is an indicator variable equal to one if the firm reports a major corporate customer. *Advertising*$_{it}$ is an indicator variable equal to one if the firm reports non-zero advertising expense, *GrowthFirm*$_{it}$, *MatureFirm*$_{it}$, *ShakeoutFirm*$_{it}$, and *DeclineFirm*$_{it}$ are indicator variables equal to one if the cash flows of the firm suggest the firm is in a growth, mature, shakeout or decline stage following Dickinson (2011). *PeerBacklog*$_{it}$ is calculated as the aggregate backlog of industry peers scaled by the aggregate sales of industry peers. *Size*$_{it}$ measures the natural log of market value of equity at the end of the fiscal year. *BM*$_{it}$ is the firm's book-to-market ratio at the end of the fiscal year. *Leverage*$_{it}$ equals the firm's market leverage ratio. *MajorExchange*$_{it}$ is an indicator variable equal to one if the firm is listed on the NYSE, AMEX, or NASDAQ. *DQ*$_{it}$ is a balance sheet disaggregation-based measure of disclosure quality, calculated following Chen et al. (2015). *FirmAge*$_{it}$ is the natural log of one plus the number of years since the firm's first fiscal year of available accounting data. *NewFirm*$_i$ is an indicator variable equal to one if the first fiscal year of available accounting data for the firm is after 1996. The model includes industry fixed effects; industries are defined using 4-digit NAICS codes. Appendix D provides complete variable definitions including data items. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (two-tailed).

Table E.2: Predictive strength of growth in order backlog for future revenue

				$MTS_{it} = 0$			$MTS_{it} = 1$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$	$\%\Delta Sales_{it+1}$
$\%\Delta Backlog_{it}$	0.141***		0.132***	0.152***		0.144***	0.097***		0.087***
	(13.25)		(11.55)	(10.73)		(9.76)	(8.09)		(7.21)
$\%\Delta Inventory_{it}$		0.136***	0.070***		0.136***	0.063***		0.136***	0.095***
		(6.06)	(3.30)		(5.54)	(2.78)		(4.32)	(3.16)
Intercept	0.067***	0.074***	0.065***	0.069***	0.076***	0.067***	0.057***	0.063***	0.056***
	(3.85)	(3.92)	(3.72)	(3.77)	(3.85)	(3.66)	(3.51)	(3.72)	(3.45)
Observations	6,761	6,761	6,761	5,455	5,455	5,455	1,306	1,306	1,306
R^2	0.099	0.023	0.105	0.107	0.022	0.111	0.068	0.027	0.080
Vuong test									
Z-statistic	7.69			7.52			1.87		
(p-value)	(0.000)			(0.000)			(0.061)		
F-test of $\%\Delta Backlog_{it} = \%\Delta Inventory_{it}$									
F-statistic			5.15			7.13			0.04
(p-value)			(0.023)			(0.008)			(0.838)

This table presents estimates of the association between growth in backlog intensity, inventory and future sales growth. $\%\Delta Sales_{it+1}$ equals the percentage sales growth from fiscal year t to $t + 1$. $\%\Delta Backlog_{it}$ measures the percentage change in backlog intensity (backlog relative to sales) from fiscal year $t - 1$ to t. $\%\Delta Inventory_{it}$ measures the percentage change in total inventory scaled by sales from fiscal year $t - 1$ to t. Firm-years are classified as following a make-to-stock business model ($MTS_{it} = 1$) if the proportion of total inventory held as finished goods is greater than 0.50. The Vuong test compares the explanatory power of $\%\Delta Backlog_{it}$ and $\%\Delta Inventory_{it}$ for each estimation sample. The F-test compares the coefficient magnitude of $\%\Delta Backlog_{it}$ and $\%\Delta Inventory_{it}$ in columns 3, 6, and 9. All variables are winsorized at the 1^{st} and 99^{th} percentiles. See Appendix D for full variable descriptions. T-statistics based on standard errors clustered by firm and year are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table E.3: Information content of order backlog for future earnings

VARIABLES	(1) E_{it+1}	(2) E_{it+1}	(3) E_{it+1}
E_{it}	0.597***	0.605***	
	(18.04)	(31.38)	
ΔOB_{it}	**0.017*** **	**0.017*** **	**0.020*** **
	(3.99)	**(7.38)**	**(8.66)**
$OpCashFlows_{it}$			0.746***
			(35.92)
$Accruals_{it}$			0.455***
			(21.16)
Intercept	0.008*	0.008***	-0.009***
	(1.84)	(5.48)	(-4.71)
Year fixed effects	No	Yes	Yes
Standard error clustering	Firm, Year	Firm	Firm
Observations	6,772	6,772	6,772
R^2	0.306	0.333	0.362

This table presents estimates of the information content of current earnings and changes in order backlog for future earnings amongst the full sample of disclosers. E_{it+1}(E_{it}) is earnings before extraordinary items in fiscal year t + 1 (t), scaled by average total assets in fiscal year t. ΔOB_{it} equals the change in order backlog from fiscal year t – 1 to t, scaled by average total assets in fiscal year t. In column 3, I divide earnings into its cash flows ($OpCashFlows_{it}$) and accruals ($Accruals_{it}$) components. All variables are winsorized at the 1st and 99th percentiles. See Appendix D for full variable descriptions. T-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table E.4: Analysts' forecast revisions

	EPS Forecasts		Sales Forecasts	
	(1)	(2)	(3)	(4)
VARIABLES	$AnalystRevision_{it}^{t+1}$	$AnalystRevision_{it}^{t+1}$	$AnalystRevision_{it}^{t+1}$	$AnalystRevision_{it}^{t+1}$
$Surprise_{it}$	0.015***	0.014***	0.078***	0.079***
	(7.27)	(7.43)	(9.37)	(9.61)
$\%\Delta Backlog_{it}$	**0.006*** **	**0.005*** **	**0.021*** **	**0.018** **
	(3.92)	**(3.03)**	**(2.93)**	**(2.55)**
$AnalystForecastAge_{it}$		0.002		0.001
		(1.25)		(0.14)
$\sigma(AnalystForecast_{it})$		-0.009***		-0.016**
		(-4.17)		(-1.97)
$\Delta AnalystFollow_{it}$		0.000		-0.000
		(0.08)		(-0.05)
$Size_{it}$		0.002***		0.002
		(4.33)		(1.03)
BM_{it}		-0.013***		-0.069***
		(-4.73)		(-5.27)
Intercept	-0.018***	-0.014***	-0.067***	-0.028*
	(-10.68)	(-3.72)	(-10.54)	(-1.66)
Observations	1,989	1,989	1,552	1,552
R^2	0.147	0.236	0.218	0.287

This table presents estimates of analysts' annual forecast revisions for EPS (Sales) in fiscal year t + 1 in columns 1 and 2 (3 and 4). $AnalystRevision_{it}^{t+1}$ measures the change in the most recent median consensus EPS (sales) forecast for fiscal year t + 1 from prior to the earnings announcement for fiscal year t to the first forecast provided within 15 days after the fiscal year t 10-K filing date, divided by the firm's stock price (market value of equity) at the end of fiscal year t. $Surprise_{it}$ is the surprise in annual EPS (sales) for fiscal year t, where the forecast was the most recent forecast provided within 30 days prior to the annual earnings announcement. $\%\Delta Backlog_{it}$ is the percentage change in backlog intensity (backlog divided by sales). $AnalystForecastAge_{it}$ is the length of time between the date most recent median consensus EPS (sales) forecast for fiscal year t + 1 prior to the earnings announcement and the earnings announcement date. $\sigma(AnalystForecast_{it})$ is the standard deviation of most recent median consensus EPS (sales) forecast for fiscal year t + 1 prior to the earnings announcement. $\Delta AnalystFollow_{it}$ is the percentage change in the number of analysts in the consensus EPS (sales) forecast for fiscal year t + 1 from the most recent consensus prior to the earnings announcement to the first consensus forecast provided within 15 days after the fiscal year t 10-K filing date. $Size_{it}$ measures the natural log of market value of equity at the end of the fiscal year. BM_{it} is the firm's book-to-market ratio at the end of the fiscal year. The regression includes year fixed effects and all independent variables (except size and BM) are decile ranked and then scaled to be between 0 and 1. $Size_{it}$ and BM_{it} are winsorized at the 1st and

99^{th} percentiles. Standard errors are clustered by firm. See Appendix D for full variable descriptions and Figure E.1 for a timeline of variable measurement for the analyst-related variables. T-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table E.5: Investment sensitivity to growth in order backlog

VARIABLES	(1) $Capex_{it+1}$	(2) $Capex_{it+1}$	(3) $Capex_{it+1}$
$Capex_{it}$	0.476***	0.476***	0.591***
	(18.90)	(18.88)	(8.94)
%Δ$Backlog_{it}$	**0.008*** **	**0.006*** **	**0.025*** **
	(5.28)	**(2.64)**	**(3.92)**
%Δ$Backlog_{it}$ × $InstOwn_{it}$		**0.007**	
		(1.57)	
%Δ$Backlog_{it}$ × E_Index_{it}			**-0.003** **
			(-2.11)
$InstOwn_{it}$		-0.001	
		(-0.56)	
E_Index_{it}			0.002**
			(2.01)
Control variables			
$Size_{it}$	0.001***	0.001***	0.001**
	(4.04)	(3.43)	(2.41)
$TobinsQ_{it}$	0.005***	0.005***	0.002*
	(5.67)	(5.73)	(1.70)
$SalesVolatility_{it}$	-0.065***	-0.063***	-0.060**
	(-3.63)	(-3.53)	(-2.53)
PPE_{it}	0.024***	0.024***	0.020***
	(7.49)	(7.53)	(4.45)
$Leverage_{it}$	0.001	0.001	0.001
	(0.33)	(0.39)	(0.13)
$CFOSale_{it}$	0.017*	0.017*	0.026**
	(1.90)	(1.84)	(2.24)
$Cash_{it}$	0.020***	0.020***	0.013**
	(4.86)	(4.91)	(2.23)
$Dividend_{it}$	-0.003**	-0.003**	-0.004***
	(-2.52)	(-2.35)	(-3.37)
$FirmAge_{it}$	-0.004***	-0.004***	-0.002*
	(-4.33)	(-4.30)	(-1.68)
$RNOA_{it}$	-0.017***	-0.016***	-0.009**
	(-5.05)	(-5.02)	(-2.40)
$Loss_{it}$	-0.005***	-0.005***	-0.001
	(-3.65)	(-3.61)	(-0.76)
Ret_{it}	0.010***	0.010***	0.011***
	(9.01)	(8.99)	(5.44)
Observations	6,402	6,402	1,778
R^2	0.540	0.540	0.596

This table provides OLS estimates of the responsiveness of a firm's capital expenditures scaled by sales ($Capex_{it+1}$) to growth in order backlog intensity (%Δ$Backlog_{it}$), which is decile ranked and scaled to be between 0 and 1. $InstOwn_{it}$ is the proportion of total common shares held by institutional owners at the end of fiscal year *t*. E_Index_{it} is the entrenchment index described in Bebchuk et al. (2009). $Size_{it}$ measures the natural log of market value of equity at the end of the fiscal year. $TobinsQ_{it}$ measures the firm's Tobin's Q ratio, which is the market value of assets relative to the book value of assets. $SalesVolatility_{it}$ is the quarterly sales volatility over the prior two years. PPE_{it} is property, plant, and equipment scaled by total assets. $Leverage_{it}$ equals the firm's market leverage ratio. $CFOSale_{it}$ equals the ratio of operating cash flows to sales. $Cash_{it}$ equals the ratio of cash holdings to total assets.

Dividend$_{it}$ is an indicator variable equal to one if the firm paid a dividend. *FirmAge*$_{it}$ is the natural log of one plus the number of years since the firm's first fiscal year of available accounting data. *RNOA*$_{it}$ is calculated as operating income after depreciation divided by average net operating assets. *Loss*$_{it}$ is an indicator variable equal to one if the firm reports a loss in earnings before extraordinary items. *Ret*$_{it}$ measures the twelve-month buy-and-hold return beginning three months after the end of fiscal year t – 1. All continuous variables (except *Ret*$_{it}$ and *RNOA*$_{it}$, which are truncated in the sample selection) are winsorized at the 1st and 99th percentiles. The model includes year and industry fixed effects. Industries are defined using 4-digit NAICS codes. See Appendix D for full variable descriptions. Standard errors are clustered by firm. T-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table E.6: Persistence of operating profitability and growth in order backlog

		High HHI_j	Low HHI_j
	(1)	(2)	(3)
VARIABLES	$RNOA_{it+1}$	$RNOA_{it+1}$	$RNOA_{it+1}$
$RNOA_{it}$	0.659***	0.637***	0.685***
	(17.16)	(17.06)	(11.71)
$RNOA_{it}$ × %Δ$Backlog_{it}$	**0.073****	**0.136*****	**-0.001**
	(2.30)	**(3.15)**	**(-0.02)**
%Δ$Backlog_{it}$	**0.109*****	**0.109*****	**0.111*****
	(10.31)	**(8.14)**	**(7.18)**
Intercept	-0.036***	-0.043***	-0.030***
	(-4.55)	(-3.87)	(-3.57)
Observations	6,402	3,098	3,304
R^2	0.477	0.475	0.480

This table provides OLS estimates of how the persistence of operating profitability varies with growth in backlog intensity. *$RNOA_{it}$* is calculated as operating income after depreciation divided by average net operating assets. *%Δ$Backlog_{it}$* is the percentage change in backlog intensity (backlog divided by sales) and is decile ranked and scaled to be between 0 and 1. In column 2 (3) I present the results of for industries in which the average concentration ratio (*HHI_j*) is greater than or equal to (less than) the median ratio in the full sample. Industries are defined using 4-digit NAICS codes. See Appendix D for full variable descriptions. T-statistics based on standard errors clustered by firm and year are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).